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Abstract: Given that structural labor supply models continue to play a key role in the process of policy design, it is important to validate their capacity to provide reasonable predictions of alternative hypothetical policy options. Comparing outcomes before and after a realized policy change (such as a tax reform) provides a source of information about behavioral response that can be used to certify the structural labor supply model. The elasticity of taxable income (ETI) measures the response in taxable income to a change in the net-of-tax rate and is a key concept in the quasi-experimental approach. The present paper shows how the ETI methodology can be used to validate predictions from a discrete choice structural labor supply model. Practical guidance is given on how such comparisons can be carried out, and results of these two main methods of obtaining empirical response estimates are contrasted and interpreted.

Keywords: Model validation, Response to tax change, Discrete choice structural labor supply model, Elasticity of taxable income

JEL classification: H21, H24, H31, J22

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Sammendrag

Strukturelle arbeidstilbudsmodeller utgjør et viktig hjelpemiddel for å analysere effekter av ulike hypotetiske endringer i skatt og overføringssystemet. Analyser av faktiske responser som følge av realiserte skatteendringer representerer en alternativ metode for å få frem kunnskap om folks responser på skatteendringer. Elastisitet av skattbar inntekt (ETI) måler responser i brutto (skattepliktig) inntekt av endringer i netto marginalskatt (1-marginalskatt), og har blitt et nøkkelbegrep innenfor den delen av litteraturen på feltet som analyserer data før og etter en skatteendring. I denne artikkelen viser vi hvordan ETI-metoden kan brukes til å validere prediksjoner fra en diskret valg arbeidstilbudsmodell (tilsvarende LOTTE-Arbeid). Vi foreslår en fremgangsmåte for sammenlikning og diskuterer metodiske forskjeller og tolkningsulikheter. Resultatet fra de to metodene samsvarer godt, og tyder på relativt små responser i arbeidstilbud for lønnstakere som følge av den norske skattereformen i 2006.

1. Introduction

Income responsiveness to tax change is a core issue in public economics. This is reflected in numerous estimates based on different methodological approaches. Public finance practitioners are often asked to predict responses to alternative policy changes, and some institutions, such as the Joint Committee on Taxation (U.S.), the Institute for Fiscal Studies (U.K.), and the Research Department of Statistics Norway, are expected to deliver empirical measures of effects to the decision-makers in their respective countries. The application of certain modeling tools is often a prerequisite for this, and the static labor supply model stands out as a practical alternative. Based on cross-sectional observations of households and individuals' consumption and connections to the labor market (typically working hours) it is possible to either directly apply a labor supply function or estimate a utility function; see the review of the literature in Blundell and MaCurdy (1999). The parameter estimates can, in turn, be used to simulate effects on working hours or incomes of hypothetical changes in the tax system.

A second main method of obtaining information about the relationship between income and taxes is based on analyses of observations before and after a realized policy reform. The identification of response estimates typically involves applying the difference-in-differences estimator or related econometric techniques. Treatment effects are measured by exploiting the fact that policy reforms can be seen as defining quasi-experiments. A tax reform generates net-of-tax rate changes along the income scale, often resulting in substantial tax changes for some taxpayers, whereas others are more or less unaffected. The elasticity of taxable income (ETI) is a key concept. It measures the response in taxable income to a change in the net-of-tax rate; see the survey of the ETI literature in Saez, Slemrod, and Giertz (2012).[1]

ETI estimates have limited value in the prediction context, because they often rely on a particular reform for identification. This makes them less applicable when assessing new policy changes.[2] The approach has gained in popularity because of its simplicity: it uses information about incomes, which is normally more easily accessible than data on working hours, and it exploits standard econometric techniques. Identification is rather challenging, however, which will be discussed in the following. The motivation underlying the ETI literature is typically to capture the full set of behavioral responses to taxation, including evasion or avoidance through tax planning. We suggest that the empirical method in the ETI literature also can be used to identify earnings responses that can be compared to

[1] By ETI studies, we refer to reduced-form studies developed over the last few decades (after initial contributions by Lindsey (1987) and Feldstein (1995)). They focus on incomes, in repeated cross-sections or in panels, before and after a major change in the tax schedule, which generates variation in tax changes across individuals.

[2] However, Carroll and Hrung (2005) and Thoresen, Bø, Fjærli, and Halvorsen (2012) are examples of studies that use estimates of the elasticity of taxable income to simulate outcomes.

the results of micro-simulations based on the structural labor supply model, and which therefore represent a source of validation for the labor supply model. Obviously, the ETI-methodology relies on certain assumptions and therefore does not necessarily uncover the "true responses" to a reform. The aim of the validation exercise is to explore the degree of correspondence between results. It is reassuring if both sources of information indicate similar response magnitudes.

Although the discrete choice labor supply model continues to be a key instrument for predicting policy changes, serious concerns have been raised about the ability of structural models to generate robust predictions about the effects of policy changes, see LaLonde (1986), Imbens (2010), and Angrist and Pischke (2010). As emphasized by Eissa and Hoynes (2006), Todd and Wolpin (2006), Blundell (2006; 2010), Keane (2010a; 2010b), and Heckman (2010), it is essential to use other sources of information to validate the models. For example, Blundell (2006) argues that "…simple difference in difference evaluations can be valuable for validating the specification of more fragile microeconometric models" (p. 425), whereas Keane and Wolpin (2007) argue pragmatically that there is no "true" decision-theoretic model, only models that are better or worse at addressing particular questions.[3] Also as recent surveys of the static labor supply literature do not seem to agree on how responsive individuals are to changes in taxes, even in the static case (see Keane and Rogerson (2012) and Chetty, Guren, Manoli and Weber (2011))[4], reconciliation of evidence from different approaches is valuable.

If the discrete choice structural labor supply model is able to produce reasonable out-of-sample predictions, we argue that it is a powerful tool for improving the informational basis for policy decisions. In this light and given the substantial efforts that have recently been put into obtaining new empirical evidence in both the structural labor supply literature and the ETI literature, it is worthwhile to cross-check results from the two approaches.

Since the main ambition of the present analysis is to show how the results of panel data analysis (using the ETI methodology) can be exploited to validate a structural model, we let earning responses (and not changes in working hours) be the focal point of the discussion. One important message is that validation cannot simply be carried out by comparing average wage elasticities from the labor supply model to average net-of-tax elasticities from the ETI approach; a nonlinear structural labor supply model produces responses that differ along the income scale, which must also be accounted for in a validation exercise.

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[3] Brewer, Duncan, Shephard and Suárez (2006), Cai, Kalb, Tseng and Vu (2008), Hansen and Liu (2011), and Pronzato (2012) are other examples of studies that describe labor supply model validations.

[4] Chetty (2012) further suggest that optimizing frictions might explain the differences between micro- and macroestimates.

The structural labor supply model discussed in the present study is a discrete choice model developed by Statistics Norway. It is related to the discrete model of van Soest (1995), see Dagsvik and Jia (2012), and Dagsvik, Jia, Kornstad, and Thoresen (2013). The model is available to Norwegian decision-makers through the model system LOTTE (Aasness, Dagsvik and Thoresen, 2007; Thoresen, Aasness and Jia, 2010). For the identification of earned income elasticities using the ETI approach, we exploit changes in the surtax schedule resulting from the 2006 Norwegian tax reform. The focus is therefore on validation of the structural labor supply model by discussing responses of wage earners at the mid-level and high-end of the income distribution. Traditional methods in the ETI literature are used, utilizing the panel structure of data to obtain individual measures of income growth, and employing instrumental variable techniques to obtain measures of change in the net-of-tax rate. To facilitate comparison, we use the discrete choice model to simulate the effects of the specific tax reform on hours of work, and use predicted income levels to obtain a comparable estimate for income elasticity with respect to the net-of-tax rate, which is the key measure in the ETI literature.

The paper is organized as follows. In Section 2, we present the two methodological approaches to obtaining tax response estimates, followed by the presentation of results in Section 3. In Section 4, we bring the results together and discuss possible caveats. Section 5 concludes the paper.

2. Empirical models for income and tax relationships

A whole range of different response estimates can be found in the labor supply literature, reflecting different theoretical models and methodological approaches. In the present analysis, we discuss evidence from two well-known static approaches:[5] tax simulation based on a structural discrete choice labor supply model, and estimation of the elasticity of taxable income by employing panel data and a quasi-experimental identification strategy. Given that estimation of structural labor supply models often involves severe econometric challenges[6] (see reviews in Blundell and MaCurdy (1999) and Keane (2011)), reduced-form estimation based on panel data could represent a more straightforward empirical technique for public finance practitioners. However, in addition to the identification methods relying on rather strong assumptions, see for example Moffitt and Wilhelm (2000), the main limitation of the ETI

[5] Chetty et al. (2011) refer to this type of evidence as steady-state elasticities. Recent surveys of the literature, such as Blundell and MaCurdy (1999) and Keane (2011), review both results of static approaches and frameworks based on life-cycle models.

[6] It can be argued that the discrete choice version of structural modeling is a more practical method than the conventional continuous approach, based on marginal calculus. The structural labor supply model associated with Hausman becomes very complicated when more general and flexible model specifications are used; see Bloemen and Kapteyn (2008).

approach is that the "treatment effect" must be interpreted in terms of the specific tax change under consideration. In general, it is therefore not informative about the effects of other policy changes. We have recently seen discussions in the literature concerning the advantages of structural modeling versus results derived from quasi-experimental research designs; see, for instance, Chetty (2009), Angrist and Pischke (2010), Deaton (2010), Heckman (2010), Heckman and Urzua (2010), Imbens (2010), and Keane (2010a; 2010b). As Chetty (2009) emphasizes, the ETI approach is not easy to place in relation to the two stereotype classifications, since the elasticities it produces share important characteristics with both strands of the literature.[7] For instance, like structural models, the ETI framework departs from an underlying utility-maximizing behavior and produces precise statements about welfare implications. The identification strategy has important similarities with experimental studies, however.[8]

Even though there are methodological concerns as regards both sources of information on tax responses, they enable cross-checking of the empirical results, which, in turn, can be employed to validate the structural model used to simulate the effects of prospective policies. In this section, we present the main characteristics of the two methods of deriving response estimates. First, we present a discrete choice labor supply model. We then describe how tax response estimates can be derived from the analysis of panel data.

2.1 Choice of working hours based on a discrete choice model formulation

Discrete choice models of labor supply based on the random utility modeling approach have gained widespread popularity,[9] mainly because they are much more practical than the conventional continuous approach based on marginal calculus; see Creedy and Kalb (2005) for a survey of the literature and van Soest (1995), Bingley and Walker (1997), Blundell et al. (2000), van Soest, Das and Gong (2002), Creedy, Kalb and Scutella (2006), Haan and Steiner (2005), Labeaga, Olivier and Spadaro (2008), and Blundell and Shepard (2012) for applications. The maximization problem for a

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[7] Chetty therefore introduces a third class, the "sufficient statistic" category, which covers studies that make predictions about welfare without estimating or specifying structural models.

[8] The early work of Feldstein (1995) is clearly close to an empirical design that relies on "treatment" and "control" groups, and uses a differences-in-difference estimation technique. However, more recent estimation methods, initiated by Auten and Carroll (1999) and Gruber and Saez (2002), can be seen as standard linear regressions with a first-differenced dependent variable and instrument for the change in the net-of-tax rate. The idiosyncrasy of the results stems from the use of one particular reform to derive estimates, which limits the applicability of estimates for other tax changes. For example, most reforms studied in the literature have involved changes in the top marginal tax rate.

[9] Despite its popularity among practitioners of labor supply analysis, less attention is devoted to this framework in recent reviews of the literature. Keane (2011), for example, essentially ignores the (static) discrete choice approach to labor supply altogether. Given that the approach is played down and only referred to as a somewhat crude approximate approach that makes estimation problems manageable, the present analysis, with its emphasis on the "job" notion, holds the promise of a coherent theoretical foundation for the discrete choice labor supply; see Dagsvik and Jia (2012) and Dagsvik et al. (2013) for more details.

person in a single-individual household can be seen as choosing between bundles of consumption (*C*) and leisure (*L*), subject to a budget constraint, $C = f(hw, I)$, where *h* is hours of work, *w* is the wage rate, *I* is non-labor income, *C* is (real) disposable income and $f(\cdot)$ is the function that transforms gross income into after-tax household income.

In the empirical specification of the labor supply model applied here, agents are assumed to make choices with respect to "job"; see Aaberge, Dagsvik and Strøm (1995), Dagsvik and Strøm (2006), Dagsvik and Jia (2012), and Dagsvik et al. (2013), where each job is characterized by a discrete set of hours, but several jobs might be characterized by the same working hours. In addition to consumption and leisure, the individual is assumed to have preferences as regards other job characteristics that are unobserved by the researcher. This means that the utility function of the household can be expressed as $U(C,h,z)$, where z = 1, 2,…, refers to market opportunities (jobs) and $z = 0$ refers to the non-market alternative. The utility function is assumed to be additively separable, $U(C,h,z) = v(C,h) + \varepsilon(z)$, where $v(\cdot)$ is a positive deterministic function and the random unobserved components $\varepsilon(z)$ are dependent on job z in addition to unobserved individual characteristics. We assume that the random components are i.i.d. extreme value distributed with c.d.f. $\exp(\exp(-x))$ for positive *x*, which implies independence of irrelevant alternatives (IIA). The strict IIA assumption is weakened, however, by allowing for random effects in relation to the wage rate.[10]

Let $\psi(h) = v(f(hw,I),h)$ be the representative utility of jobs with hours of work *h*, a given individual specific wage rate *w,* and non-labor income *I* (for simplicity, *w* and *I* are suppressed in the notation). We further assume that individuals face restrictions on the set of available market opportunities. Let $B(h)$ denote the agent's set of available jobs with hours of work *h*, and $m(h)$ define the number of jobs in $B(h)$. We assume that there is only one non-market alternative, so that $m(0) = 1$.

Now, let *D* be the set of possible hours of work. Then, by applying standard results in discrete choice theory (McFadden, 1984), it follows that the probability that the agent will choose job *z* can be expressed as

$$(2.1) \qquad P\left(v(f(hw,I),h) + \varepsilon(z) = \max_{x \in D \cup \{0\}} \max_{k \in B(x)} (v(f(xw,I),x) + \varepsilon(k)) \right)$$

[10] The wage rate is replaced by a wage equation that includes a stochastic error term, and thus a mixed multinomial logit model follows, see McFadden and Train (2000) and Haan (2006).

$$= \frac{\exp\psi(h)}{\sum_{x\in D,}\sum_{z\in B(x)}\exp\psi(x)+\exp\psi(0)}.$$

Further, we derive an expression for the probability of choosing any job with hours of work *h* by adding all the alternatives within $B(h)$.

(2.2) $$\varphi(h)=\sum_{z\in B(h)}\frac{\exp(\psi(h))}{\sum_{x\in D,}\sum_{z\in B(x)}\exp(\psi(x))+\exp(\psi(0))}=\frac{\exp(\psi(h))m(h)}{\exp(\psi(0))+\sum_{x\in D}\exp(\psi(x))m(x)},$$

When $h = 0$, we get

(2.3) $$\varphi(0)=\frac{\exp(\psi(0))}{\exp(\psi(0))+\sum_{x\in D}\exp(\psi(x))m(x)}.$$

The number of jobs with hours of work *h*, $m(h)$, can be decomposed into $\theta g(h)$, where θ_i defines the total number of jobs available to the individual and $g(h)$ is the fraction of jobs available to the agent with offered hours of work equal to *h*. We will call $m(h)$ the opportunity measure and $g(h)$ the opportunity distribution. By inserting the decomposed opportunity measure into the expressions for probabilities, we obtain

(2.4) $$\varphi(h)=\frac{\exp\left(\psi(h)\right)g(h)\theta}{\exp\psi(0)+\theta\sum_{x\in D}\exp\psi(x)g(x)},$$

and

(2.5) $$\varphi(0)=\frac{\exp\left(\psi(0)\right)}{\exp\psi(0)+\theta\sum_{x\in D}\exp\psi(x)g(x)}.$$

The resulting expression is a choice model that is analogous to a multinomial logit model with representative utility terms, $\psi(h)$, weighted by the frequencies of available jobs, $m(h)=\theta g(h).$ To identify the model, we assume for the sake of simplicity that the number of jobs available, θ_i, is a function of years of education and that the opportunity distribution, $g(h)$, is constant over *h* apart from a possible peak for full-time. The empirical specification of this model turns out to be similar to van Soest's model (1995), although the rationalization for introducing state-specific dummy variables is an important extension.

Appendix B shows how $\psi(h)$ and the wage rate are specified. It presents the estimation results for single males, single females, and, separately, for males and females in couples (married/cohabiting). They are utilized in the simulation of labor supply responses to the Norwegian tax reform of 2006, presented in Section 3.

2.2 Utilizing direct observations of income growth

The approach taken in much of the ETI literature departs from an underlying utility-maximizing behavior similar to that seen in the standard labor supply literature above (Feldstein,1999; Blomquist and Selin, 2010; Saez, Slemrod and Giertz, 2012). Individuals are assumed to maximize a utility function that increases in consumption (*C*) and decreases in taxable income (*q*), subject to a budget constraint described by $C = (1-\tau)q + R$, where τ is the marginal tax rate (which applies to a linear segment of the tax schedule), and *R* is virtual income. Accordingly, the "supply function" of taxable income is estimated as a function of the marginal tax rate and virtual income. The formulation thus suggests a closer relationship to the part of the structural labor supply literature that is based on estimation of a continuous labor supply function with a piecewise-linear budget constraint, as in Burtless and Hausman (1978), and Hausman (1985).[11]

Moreover, whereas standard labor supply approaches usually focus on the choice of hours of work (*h)* given an individual-specific wage rate, a main motivation for the ETI approach is that it allows for a broader range of responses to changes in marginal tax rates, such as tax avoidance and evasion captured by the taxable income response, as denoted by Feldstein (1995). In the present context, we define taxable income *q* as earned income, generated by the wage rate (*w*) times hours of work (*h*).[12] Earnings responses to the marginal tax rate can be identified since we analyze a reform period with changes in the tax schedule for labor income.[13]

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[11] The Hausman approach thus deviates from the standard discrete choice model (van Soest, 1995), in which estimation is carried out directly on the utility specification.

[12] Separation into measures of wage and working hours is not possible with our panel data set.

[13] In the Norwegian context, labor income is not subject to deductions and therefore equals taxable labor income, so that responses in the form of tax avoidance and deduction behaviour are not relevant.

Panel data covering a period of net-of-tax rate variation across individuals and across time (often covering a tax reform) have been the main data source for the identification of ETI-estimates. We let pre-tax income for individual *i* at time *t*, q_{it}, be explained by a time-specific constant, κ_t, the net-of-tax rate, $log(1\text{-}\tau_{it})$, unobserved heterogeneity μ_i and the remaining iid error term, ξ_{it},

(2.6) $$\log q_{it} = \kappa_t + \lambda \log(1-\tau_{it}) + \mu_i + \xi_{it} ,$$

The basic framework for identification in the ETI literature consists of various estimations of a first-differenced version of (2.6), using panel data for two periods,

(2.7) $$\Delta \log q_i = \kappa + \lambda \Delta \log(1-\tau_i) + \Delta \xi_i .$$

The coefficient of interest, λ, measures the elasticity of income with respect to changes in the net-of-tax rate defined as $\frac{1-\tau}{q}\frac{\partial q}{\partial(1-\tau)}$. The reliability of results depends on carefully framed empirical designs for the identification of the key parameter, including controls for individual characteristics that might affect income growth. One main methodological identification challenge (w.r.t. λ) has been the endogeneity of the tax rate, which has led to the estimation of (2.7) using IV techniques, for instance employing the difference-in-differences estimator, and grouping individuals into treated and non-treated groups based on pre-reform income levels. Feldstein (1995) is an example of this.[14] Many post-Feldstein studies employ a closely related exclusion restriction, using the change in net-of-tax rates based on a fixed first period income as instrument in an IV regression; see Auten and Carroll (1999) and Gruber and Saez (2002). Thus, as already noted, the ETI literature is related to methods commonly used in the "experimentalist" or "program evaluation" literature; see, for instance, Imbens and Wooldridge (2009). However, as tax reforms typically involve a reduction or increase in top marginal tax rates and small or no changes at lower income levels, the treatment and control groups follow from their income levels. We are thus far from an ideal randomized trial situation.

The estimated elasticity can be interpreted as the average treatment effect for the treated. In other words, if we let a parameter δ be a zero-one indication of being treated (experiencing net-of-tax rates changes, or not), as in Feldstein (1995), we identify $E(\lambda | \delta_{it} = 1)$. According to Blundell and MaCurdy

[14] Feldstein (1995) used a table version of this technique. Aarbu and Thoresen (2001) employed a regression version of the same procedure as one of two econometric methods. See also Holmlund and Söderström (2011) and Vattø (2013) for studies that analyze the timing of responses by introducing dynamics in the model specification.

(1999), this parameter is subject to conventional sample selection biases and cannot as a rule be used to simulate policy responses.[15] Irrespective of this discussion, we focus on the use of ETI as a quasi-experimental method to validate the predictions from a structural model, as suggested by, e.g., Blundell (2006).

3. Tax response estimates

In this section, we probe deeper into the cross-checking of the results of the two methodologies, discuss the empirical content of the two sources of information and, finally, assess the validity of the structural discrete choice model. The change in marginal tax rates for wage income as a result of the Norwegian tax reform of 2006 is used to illustrate the effects. After presenting the tax reform, which serves as a tool for the identification of tax behavioral responses, we present the evidence from the panel data approach, and these results are then compared to the predictions of the labor supply model.

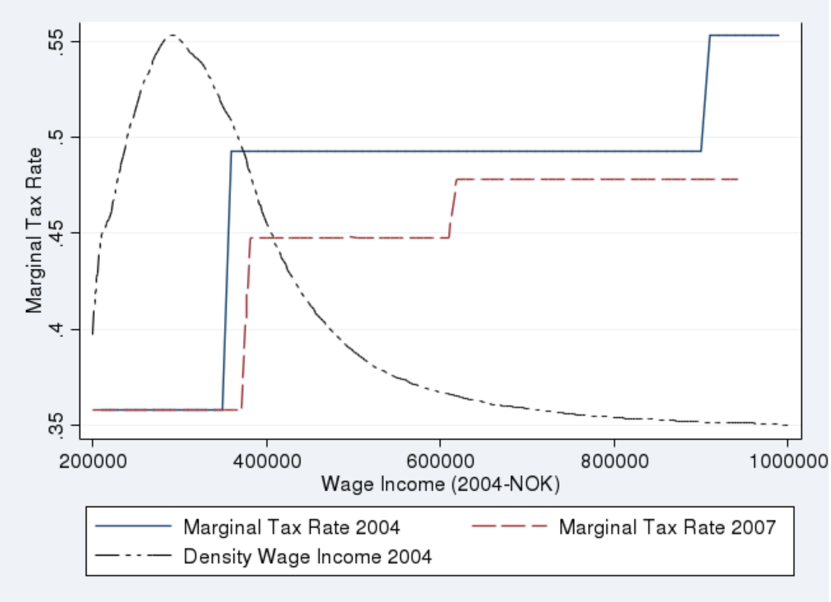
3.1 The reductions in marginal tax rates as a result of the tax reform of 2006

Norway has a “dual income tax” system, enacted through the 1992 tax reform, which consists of a combination of a low proportional tax rate on capital income and progressive tax rates on labor income. The system proliferated in the Nordic countries in the early 1990s. The Norwegian version had a flat 28 percent tax rate levied on corporate income, capital income and labor income coupled with a progressive surtax applicable to labor income. The gap between marginal tax rates on capital income and wage income was problematic, and the schedule was reformed in 2006 in order to narrow the differences, by introducing shareholder income tax, and, most importantly in the present context, by cutting marginal tax rates for labor income.

The tax reform was gradually implemented in 2005 and 2006; in Figure 1 we compare schedules for 2004 (pre-reform) and 2007 (post-reform). The figure shows the principal features of the Norwegian labor income tax system: a two-tier surtax that supplements a basic income tax rate of 28 percent plus a 7.8 percent social insurance contribution. In 2004, the first tier of the surtax was applied to incomes above NOK 354 300 at a rate of 13.5 percent, and the second tier of 19.5 percent applied to income in excess of NOK 906 900. The reform meant that the maximum marginal tax rate fell from 55.3 to 47.8 percent, but became effective at a lower level.

[15] The estimated elasticities can only be used to simulate hypothetical tax reforms under the assumption that the elasticity is constant over the income distribution, which is clearly not consistent with findings from the structural labor supply literature.

Figure 1. Reductions in marginal tax rates as a result of the tax reform



3.2 Evidence from panel data estimations

In the following, we closely follow the conventional approach in the ETI literature; see, e.g., Gruber and Saez (2002). The main data source is the Income Statistics for Persons and Families (Statistics Norway, 2005), a register-based data set that covers the whole Norwegian population, with data from income tax returns as the main component. We limit the data set to wage earners over the period 2000-2008,[16] utilizing overlapping three-year individual differences. More details on the empirical specification and sample restrictions are provided in Appendix A.

Changes in net-of-tax rates are instrumented by using the tax change for a constant base year income (referring to the first year in each three-year difference). Since the tax instrument is constructed from the base year income and the dependent variable is growth in income (over the same three-year period), a control is necessary for mean reversion and drifts in the income distribution. Mean reversion in this context refers to an observed negative correlation between initial income and income growth due to transitory shocks in income, whereas changes in the income distribution can lead to correlations in both directions. These phenomena should not be mistakenly attributed to the exogenous tax change. As a solution, Auten and Carroll (1999) included the base year income in logs as an additional explanatory variable, whereas Gruber and Saez (2002) extended this approach by allowing for a

[16] We analyze a somewhat longer time period than only the actual tax reform period (2004-2006) in order to improve the estimates for the non-tax-related control variables.

piecewise linear function of base year income. Here, 10 linear splines or a third degree polynomial of base year income are used to control for mean reversion and drifts in the income distribution.[17]

Table 1 shows the results of the 2SLS regressions. To address the mean reversion problem, in the first two columns, we have included 10 splines of log income, and, in the third and fourth column, a third degree polynomial of log income. Specifications (2) and (4) include a control for virtual income, following Blomquist and Selin (2010), see also Appendix A. Although results (in general) are sensitive to the inclusion of the mean reversion control, there is only a small difference between the estimates including 10 splines or a third degree polynomial of base year income. The uncompensated elasticity of earnings with respect to net-of-tax is estimated to be about 0.05–0.06 without the income effect, and 0.03–0.04 after the income effect is controlled for. The income elasticity is small and negative, as expected.

Table 1. Estimates of the net-of-tax rate elasticity for earned income. 2SLS regression results for all wage earners, standard errors in parentheses

	Mean reversion control			
	Splines		Polynomial of log income	
	(1)	(2)	(3)	(4)
Net-of-tax rate elasticity	0.0562***	0.0370***	0.0531***	0.0356***
	(0.0023)	(0.0032)	(0.0023)	(0.0031)
Income elasticity		-0.0091***		-0.0105***
		(0.0012)		(0.0012)
Number of observations	4 933 291	4 331 276	4 933 291	4 331 276

Note: All regressions include control variables for gender, wealth, age, age squared, married, number of children under and above the age of 6, newborn, residence in Oslo/ densely populated area, non-western origin, years of education, 9 dummies for field of education, income shifting control and year dummies. Full regression output is reported in Table A.1, Appendix A. *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

Table 2. Estimates of the net-of-tax rate elasticity for earned income. 2SLS regression results for separate groups of wage earners, standard errors in parentheses

	Single females	Single males	Females, couples	Males, couples
Net-of-tax rate elasticity	0.0377***	0.0395***	0.0441***	0.0547***
	(0.0061)	(0.0059)	(0.0049)	(0.0031)
Number of observations	576 232	959 151	1 109 651	2 287 960

Note: All regressions include control variables for wealth, age, age squared, married, number of children under and above the age of 6, newborn, residence in Oslo/ densely populated area, non-western origin, years of education, 9 dummies for field of education and year dummies. Full regression output is reported in Table A.2. *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

The estimated (average) net-of-tax elasticities are small compared to most other ETI studies. According to Saez, Slemrod and Giertz (2012), estimates from the U.S. (after Feldstein, 1995) range

[17] In addition we alleviate the problem of mean reversion by excluding observations with low base year income (below percentile 33), see Appendix A.

from 0.12 to 0.40. Our estimates, however, measure the responses in wage earnings only, and do not identify responses in avoidance and reporting behavior. The estimates are in line with Kleven and Schulz (2011), who report elasticities of approximately 0.05 for wage earners in Denmark.

Further, we divide the sample into four groups: single females, single males, females in couples, and males in couples. Response estimates for specific groups facilitate closer comparison with the simulation results from the structural model estimation. A third degree polynomial is used as a mean reversion control and the additional controls for virtual income[18] and income shifting (see Appendix A) are excluded. The results in Table 2 suggest that the responses are positive small, 0.04-0.05, but statistically significant for all four groups of wage earners.

3.3. Results of simulations based on labor supply model

Next, we show how we can derive estimates of comparable net-of-tax rate elasticities from a labor supply model simulation to assess to which extent the discrete choice model replicates the results of the ETI-analysis.

The discrete choice structural model is estimated by using information on hours of work from the Labor Force Survey (Statistics Norway, 2003) and income data from the Income Statistics for Persons and Families (Statistics Norway, 2005) for 2004 (a pre-reform year). Four separate specifications, for men in couples, women in couples, single women and single men, are estimated. The results of the labor supply model estimations are presented in Appendix B, including the results of the estimations of wage rate equations.

Before addressing the results of simulations of the earned income elasticity with respect to the net-of-tax rate, we present standard wage elasticities from the estimated model. The uncompensated wage elasticities are obtained by increasing the gross hourly wage by one percent and using the model and parameter estimates to simulate the percentage change in predicted hours worked for each individual. The average elasticity for each group is shown in Table 3. Further, the wage elasticity is decomposed into a participation elasticity and an elasticity conditional on participation, measuring the extensive

[18] Income effects are often neglected in the ETI literature, under the assumption that the effect is close to zero, as found in e.g. Gruber and Saez (2002). Moreover, there is no standardized method of constructing income controls. We have relied on a method proposed by Blomquist and Selin (2010) that includes non-labor income, and therefore seems most appropriate for our setting. However, it turns out to be problematic that the two excluded instruments for net-of-tax rate and virtual income are similarly constructed and therefore appear to suffer from a problem of collinearity, in particular when categorizing into homogenous groups of individuals. We have therefore omitted income effects in Table 2.

and intensive margin, respectively. The results for the intensive margin are most relevant with respect to the results of the ETI framework. They show modest elasticities, in the range 0.10–0.29.

Table 3. Wage elasticity estimates derived from simulation of structural labor supply model, standard errors in parentheses

	Wage elasticities		
	Total	Extensive margin	Intensive margin
Males in couples	0.16*** (0.0081)	0.005*** (0.0013)	0.15*** (0.0079)
Single males	0.11*** (0.0137)	0.010*** (0.0019)	0.10*** (0.0121)
Females in couples	0.38*** (0.0107)	0.090*** (0.0051)	0.29*** (0.0079)
Single females	0.21*** (0.0197)	0.052*** (0.0076)	0.16*** (0.0195)

Note: Standard errors obtained by non-parametric bootstrapping, 30 repetitions.

Table 4. Predicted weekly hours of work, pre- and post-reform, derived from simulation of labor supply model, standard errors in parentheses

	Pre-reform working hours	Post-reform working hours	Difference
Males in couples	38.96 (0.041)	39.27 (0.051)	0.81 %
Single males	39.01 (0.078)	39.25 (0.088)	0.62 %
Females in couples	36.26 (0.066)	36.39 (0.069)	0.41 %
Single females	37.22 (0.088)	37.33 (0.093)	0.30 %

Note: Standard errors obtained by non-parametric bootstrapping, 30 repetitions.

Note that the elasticity of working hours with respect to the wage rate (for a given tax rate)[19] is conceptually equal to the elasticity of earnings with respect to the net-of-tax rate (for a given wage rate). However, as the labor supply model is non-linear, obtaining net-of-tax rate elasticities (as measured by the ETI method) requires that the particular reform used for identification must be taken into account. To approach comparable measures, we therefore let the results of labor supply model simulations enter into a regression, similar to that seen in the ETI literature (see Section 2.2). First, the structural model is used to simulate the pre-reform and post-reform working hours; average estimates for the four groups of wage earners are shown in Table 4. Growth in labor income is identical to growth in predicted hours for an individual-specific wage rate. Then, measures of the change in the net-of-tax are derived from the predicted income levels, and instrumented using similar methods as in the ETI literature: the change in net-of-tax for constant (predicted) initial labor income (predicted pre-reform hours times the individual's constant wage rate),[20] see the results in Table 5.

[19] To be accurate, the wage elasticities measured above are gross wage elasticities, where the increase in wages might increase the tax rate as well.

[20] Predicted working hours follow from the individual's probability distribution, using a draw from a uniform distribution (the same draw applies for each individual pre- and post-reform). An alternative method is to use the expected predicted working hours estimate for each individual pre- and post-reform. This leads to similar results, although the income distribution becomes more compressed. As in the panel data analysis, the regression is restricted to individuals with predicted pre-reform income in percentile 33 or above.

Table 5. Estimates of the net-of-tax rate elasticity derived from labor supply model simulation

	Net-of-tax rate elasticity	Std. error
Males in couples	0.092***	(0.0051)
Single males	0.076***	(0.0068)
Females in couples	0.055***	(0.0037)
Single females	0.052***	(0.0039)

Note: Standard errors obtained by non-parametric bootstrapping, 30 repetitions.

In the next section, we present a comparison of the results of Table 5 with the results of the panel data analysis. At this stage, we observe that the net-of-tax rate elasticities are lower than the wage elasticities (see Table 3), ranging between 0.05 and 0.09. Although the estimated wage elasticities were clearly higher for women in couples (0.29 versus 0.10–0.15 for males), the estimates of the net-of-tax rate elasticities suggest that responses are larger for males than females. This indicate that males at the high end of the income distribution are on average more sensitive than high-income females to the particular change in the tax schedule exploited to derive the net-of-tax rate elasticities (changes in the top marginal tax rates).

4. Reconciling the evidence

As described in the previous section, we obtained net-of-tax rate elasticities from the discrete choice model that can be compared to the results of a traditional ETI analysis. One should be aware, however, of important differences between the discrete choice labor supply model and the underlying framework leading to the ETI approach. Before comparing the results of the two approaches, let us therefore review some of the main differences, such as discrete/continuous choice, responses through working hours/taxable income, the underlying time frame and, more generally, the distinction between a structural approach (used for simulation) and a reduced form panel data analysis.

Firstly, the structural labor supply model we have estimated is based on discrete choice instead of marginal optimization, generating a probability distribution for different working hours options.[21] There are different procedures that can be employed in the simulation of such models, all of which respect the probabilistic nature of the model. The present model describes the effects of alternative policies by letting the overall probability distribution be altered as the economic conditions change. Since it is the probability distribution that describes the choices of different policy alternatives, all individuals are affected by a reform to some extent. In the ETI literature, the response estimates reflect

[21] The probability distribution follows from McFadden's conditional logit framework, see for instance McFadden (1984). Recall that the particular labor supply model presented here is a "job choice" model, which is turned into a choice between different categories of hours of work.

(in a somewhat simplified manner) the policy change exploited to obtain estimates, dividing the data into "treated" and "less or not treated", based on marginal optimization. In this perspective the modeling of the ETI literature is therefore more related to the perspective of continuous hours structural labor supply models such as the socalled Hausman model, see Section 2.2.

Secondly, the models differ in the type of responses that tax changes induce. As already emphasized, the ETI literature includes a whole range of responses, including tax planning and tax avoidance, as it typically focuses on total taxable income. In our study, we have a more narrow focus on wage earners' responses in the form of labor income (hourly wage times hours). We should still capture responses in both working hours and the wage rate. In the ETI literature, the wage rate is seen as a choice variable for the individual, as he or she can alter his/her wages through increased efforts per hour or by changing jobs. In the labor supply literature, the wage rate is typically considered to be fixed at the individual level. There have been some attempts to endogenize the wage rate in labor supply models (see for example Moffitt, 1984), but still not assuming that the wage rate can be altered by decisions relating to individual effort.

Thirdly, the methods differ with respect to the time frame. The structural model is a static model where a new long-run steady-state is immediately attained. To obtain estimates of the ETI, on the other hand, we use the ad hoc choice of three-year spans. Because the structural model might be inappropriate for describing short-term responses, it is not obvious how such results can be compared to the standard time framing in the ETI literature.

Finally, it is important to warn against giving precedence to either of the two empirical approaches presented here. The structural labor supply model is based on a model for optimizing behavior, whereas the panel data analysis yields an average effect for the treated of the reform used for identification. The advantage of the structural approach is that the model can be used for any hypothetical tax reform, and it should have high general applicability because it endeavors to estimate the deep underlying structural parameters. However, because the model might be too simple or suffer from misspecification, the data-driven results of the ETI approach might serve as a test of how well the structural model performs. As is evident from the experience of ETI estimations, however, the results cannot be characterized as uncovering "true responses". Ideally, we would not only require pre- and post-reform data, but also counterfactual income levels in the case where no reform occurred. Given the lack of counterfactuals, one of the main practical problems of the ETI approach we have adopted here is that the tax rate instrument is correlated with other explanatory variables for wage growth, such as mean reversion and trends in the income distribution, that are unrelated to the tax reforms.

Despite the major differences in the methodological framework, ETI estimates represent an information source for validation of the simulation model, and in Table 6 we restate the comparable results of the structural model and the experimental panel data estimation.[22] The measured net-of-tax rate elasticities are small in both the structural and the panel data analysis, within the range 0.04–0.09. The results are in line with the argument that high-income individuals are less responsive to tax changes, as there is a natural or institutional limit on working hours per week. Our estimates are smaller than typically found in the ETI literature, possibly because we focus on wage earnings in contrast to overall taxable income. Moreover, we look at a strictly defined group of prime age wage earners, with wage income in the median and upper part of the income distribution. This group might be less responsive than self-employed people, people with capital income, and individuals with a less strong attachment to the labor market. In general, it might be argued that the Norwegian institutional setting produces smaller elasticities. The argumentation presented in Slemrod and Kopczuk (2002) can be used in support of the notion that Norwegians are less responsive.[23]

It is surprising that the structural model predicts somewhat larger responses than the panel data approach; we would expect the panel data estimates to be larger, since a broader measure of responses is arguably captured through earnings. However, the magnitudes of the estimates are indeed very similar. Moreover, larger estimated responses for married males than for females are in line with the predictions of the labor supply model for the particular tax reform under consideration.

Table 6. Comparison of net-of-tax rate elasticity estimates from structural labor supply model simulation and analysis of panel data. Standard errors in parentheses

	Structural model	Panel data
Males in couples	0.092*** (0.0051)	0.055*** (0.0031)
Single males	0.076*** (0.0068)	0.040*** (0.0059)
Females in couples	0.055*** (0.0037)	0.044*** (0.0049)
Single females	0.052*** (0.0039)	0.038*** (0.0061)

[22] For both methods, we estimate the uncompensated elasticities. The income effect is typically estimated to be small in the ETI literature, and it is often assumed that the compensated and uncompensated elasticities are similar, see e.g. Saez, Slemrod and Giertz (2012). Measures of compensated elasticities are rare in the discrete choice structural labor supply literature; see, however, Dagsvik and Karlström (2005) for a method of obtaining compensated effects.

[23] For instance, in order to be able to uphold a progressive tax system, egalitarian societies may establish institutions to reduce tax avoidance.

5. Conclusion

The discrete choice labor supply model is a tool that is frequently used to analyze a wide range of hypothetical tax and benefit reforms. Given its key role in the decision-making process, it is important to validate its capacity to provide reasonable descriptions of the effects of prospective policies. There has recently been growing interest in validating discrete choice structural models using natural experiments. However, we have yet to see any detailed discussion of how the standard structural labor supply model can be validated using results from the ETI literature. In this perspective, the present study offers a procedure for comparison.

A validation that is simply based on comparisons of average wage elasticities from the labor supply model with average net-of-tax rates from the ETI approach is in danger of being misleading. The reason is that ETI estimates are derived from specific tax reforms, and that they therefore measure the average effects for the individuals treated by the reforms. The nonlinearity of the labor supply model, on the other hand, implies different responses along the income distribution.

In this study, we have shown how a version of the labor supply model made available to Norwegian decision-makers (through the model system LOTTE) is validated by ETI estimates. The model is used to simulate the labor supply effects of the Norwegian tax reform of 2006. Earnings are simulated pre- and post-reform under an exogenous wage assumption, and the regression framework of the ETI literature is used to obtain a net-of-tax rate elasticity for the simulated earnings level. These estimates have then been compared with ETI estimates obtained in the conventional manner, using panel data of actual labor income levels before and after the reform.

Our main finding is that simulations from the structural labor supply model yield net-of-tax elasticity estimates that are close to the elasticity estimated on the basis of the panel data: ranging from 0.05 to 0.09 for the structural model and 0.04 to 0.055 for the panel data analysis. We thus find it reassuring that the predictions of the labor supply model are not far from the results of the panel data analysis.

Even though some doubts have been expressed about the capacity of the structural prediction model to predict outcomes of policy changes, it continues to be a main tool for public finance practitioners. Instead of dismissing the approach as a means of obtaining policy guidance, more effort should be put into qualifying models through validation. The present study is just one example among many possible certifications of this key instrument.

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Appendix A. Empirical specification for panel data analysis

A general specification

As discussed in Section 2, the standard framework for estimation of the elasticity of taxable income is to employ panel data information, estimating a model in differences, typically for a three-year span. We stack observations for each three-year difference (2000-2003, 2001-2004, .. , 2005-2008) over the period 2000-2008, and add time invariant explanatory variables as possible explanations for income growth. Thus, the three-year difference in (log) taxable income, q_{it}, is explained by a period-specific effect, κ_t, differences in marginal tax rates, $1-\tau_{it}$, and a set of control variables, X_{it}.

(A.1) $$\log\left(\frac{q_{it+3}}{q_{it}}\right) = \kappa_t + \lambda_1 \log\left(\frac{1-\tau_{it+3}}{1-\tau_{it}}\right) + X_{it}\omega + \xi_{it}$$

The key parameter is λ_1, which measures the uncompensated elasticity of taxable income.

We estimate the model by using panel data derived from administrative registers, with Income Statistics for Persons and Families as our main source (Statistics Norway, 2005). The income register contains information for the whole population of Norway (about 4.6 million in 2004). As for the structural model, we limit the sample to wage earners aged 25-62 years, defined as having wage income as their main source of income, and we exclude individuals with positive income from self-employment or pensions. In addition, we limit the sample to individuals with taxable labor income above percentile 33 (about NOK 250 000 in 2004) in the base year (the first year in each three-year difference). We are left with about five million three-year differences.

There are two reasons for excluding the lower income levels. Firstly, we are mainly interested in the effect of decreased surtax rates, which only affect about 1/3 of the wage earners. Secondly, the mean reversion problem (described in more detail below) is especially severe for individuals who initially had low income, which makes this group less appropriate as a control group.

The dependent variable is growth in gross labor income, the same income concept that forms the tax base for labor taxation. The elasticity we obtain can therefore be denoted as the elasticity of earned income. The actual marginal tax rate is not immediately available in the data set, but is constructed by a tax simulation program based on the additional taxes levied on the individual if the income is increased by five percent. The change in marginal tax rate is clearly endogenous, since the marginal tax rate (as a function of income) is jointly determined with income. The tax rate change, $\log\left[(1-\tau_{it+3}(q_{it+3}))/(1-\tau_{it}(q_{it}))\right]$, is therefore instrumented by a tax rate change for a "constant" or inflation-adjusted initial income level, $\log\left[(1-\tau_{it+3}((1+b)q_{it}))/(1-\tau_{it}(q_{it}))\right]$, where *b* corresponds to median income growth over the period *t* to *t+3*.

The error term of A.1 is most likely correlated with first period income, q_{it}, for instance because of mean reversion and drifts in the income distribution (Moffitt and Wilhelm, 2000). For example, some individuals with high income in period *t* and therefore (mistakenly) placed in the treatment group with large reductions in marginal tax rates, will return to their normal income level in period *t+3*, and an income reduction will be recorded. To account for the mean reversion bias, Auten and Carroll (1999) suggest adding $\log q_{it}$ as an additional control variable. As shown in many analyses, Aarbu and Thoresen (2001) included, this control has a big influence on tax elasticity estimates, and it shifts estimates of the change in the net-of-tax rate from negative to positive. Gruber and Saez (2002) suggest extending the base period income control technique by including a piecewise linear function of $\log q_{it}$.

The main problem of employing rich controls for mean reversion based on first-period information is that identification of the effect of the net-of-tax rate may become blurred, because the mean reversion control and the tax change instrument depend on the same variable; see, for instance, Saez, Slemrod, and Giertz (2012). The problem is alleviated by including periods both with and without tax changes. Our empirical study also benefits from having other sources of variation in the tax rate than income alone, in view of two tax classes and a separate schedule for northern Norway.

The spline or polynomial function in the log of first period income is not just a control for mean reversion effects along the income scale; it can also be seen as accounting for changes in the income distribution. For example, a trend towards increasing inequality may result in a spurious correlation between lowered tax rates for high-income individuals and income growth rates.

Individual characteristics are included to control for non-tax-related income evolution over time or over the lifecycle. We have had access to a number of socio-demographic characteristics, such as age, years of education, field of education, marital status, number of children, geographical location, and area of origin. The regression output confirms that the presence of young children seems to limit income growth, whereas length of education has a positive effect, presumably due to a steeper increase in earnings over the lifecycle.

The Norwegian tax reform of 2006 reduced the tax advantages enjoyed by capital income compared to labor income, and it could therefore result in a reversed income-shifting effect where individuals again increase their labor earnings at the expense of capital income; see Thoresen and Alstadsæter (2010) for the measurement of the opposite effect. In the pooled regressions, we control for this possible effect by including an interaction of the individual's log capital income in the base year period with the flat tax rate change in capital income over the three-year period under consideration.[24]

The income effects are often neglected in the literature, since the income elasticity is assumed to be small (as shown by Gruber and Saez, 2002). To test this, we include a virtual income control in some of the main specifications. Like Blomquist and Selin (2010), we construct virtual incomes using procedures seen in the labor supply literature, based on piecewise linear approximations to the budget constraint (see Burtless and Hausman, 1978). Virtual income, $R_{it} = I_{it} + \left(\tau_{it} q_{it} - \upsilon_{it}(q_{it})\right)$, is expressed as the difference between paying the marginal tax on overall labor income, $\tau_{it} q_{it}$, and the actual taxes paid, expressed as $\upsilon\left(q_{it}\right)$. This difference is positive in a progressive tax system with tax allowances. In addition, since q_{it} only captures labor income, non-labor income, I_{it}, is included and assumed to be exogenously given. In non-labor income, we include transfers such as child benefit and other social transfers, in addition to net-of-tax capital income. For couples, non-labor income includes the disposable income of the spouse. Since the model is estimated in first differences, the change in virtual and non-labor income, *R*, is instrumented by (again) using the exogenous tax rate change for a fixed income level.

Estimation results

Table A.1 shows the full regression output of our main results. In the first set of regressions, (1) and (2), we have included log base year income as a linear function, in the second, (3) and (4), as a 10-piece spline, and, in the third, (5) and (6), as a centered third degree polynomial. We present the results both with and without control for virtual income.

We find specifications (3)–(6) most convincing, as we believe it is not sufficient to include a linear control for the occurrence of mean reversion.[25] We see that the results are less influenced if either splines or polynomials are used as control variables.

[24] Note that this control variable is not endogenous, since the tax rate is flat and therefore identical for all wage earners. The control variable has the value 0 in periods where no capital tax changes occurred.

[25] When only a linear control is included for mean reversion, the estimated elasticity becomes dependent on sample restrictions.

Table A.1. Estimates of the net-of-tax rate elasticity for earned income. 2SLS regression results for all wage earners, standard errors in parentheses

	Mean Reversion Control					
	Log base year income		10 Splines of base year income		3rd degree polynomial of base year income	
	(1)	(2)	(3)	(4)	(5)	(6)
Net-of-tax rate elasticity	0.0312***	0.0154***	0.0562***	0.0370***	0.0531***	0.0356***
	(0.0021)	(0.0030)	(0.0023)	(0.0032)	(0.0023)	(0.0031)
Virtual income elasticity		-0.0094***		-0.0091***		-0.0105***
		(0.0012)		(0.0012)		(0.0012)
Income shifting control	0.0112***	0.0107***	0.0111***	0.0106***	0.0111***	0.0105***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Male	0.0412***	0.0333***	0.0418***	0.0338***	0.0416***	0.0337***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Wealth	-0.0003***	-0.0002***	-0.0003***	-0.0002***	-0.0003***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	0.0015***	0.0010***	0.0015***	0.0010***	0.0015***	0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age squared	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married	0.0114***	0.0097***	0.0113***	0.0095***	0.0112***	0.0096***
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Newborn	-0.0592***	-0.0500***	-0.0596***	-0.0503***	-0.0595***	-0.0502***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
No. children under age 6	0.0202***	0.0181***	0.0202***	0.0181***	0.0202***	0.0182***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
No. children above age 6	0.0081***	0.0085***	0.0082***	0.0086***	0.0081***	0.0086***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Non-western origin	-0.0431***	-0.0420***	-0.0432***	-0.0421***	-0.0432***	-0.0421***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Residence in Oslo	0.0024***	0.0012***	0.0023***	0.0012***	0.0024***	0.0013***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Densely populated area	0.0096***	0.0093***	0.0096***	0.0093***	0.0096***	0.0093***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Years of education	0.0133***	0.0127***	0.0133***	0.0126***	0.0133***	0.0126***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Field of education	Yes	Yes	Yes	Yes	Yes	Yes
$\log(\text{income}_{it}/\text{median}_t)$	-0.1124***	-0.1055***				
	(0.0004)	(0.0004)				
10 linear Splines			Yes	Yes		
3 polynomial					Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.0192***	0.0055	-0.0174***	0.0069	-0.0182***	0.0074*
	(0.0029)	(0.0031)	(0.0034)	(0.0036)	(0.0029)	(0.0031)
Number of observations[a]	4 933 291	4 331 276	4 933 291	4 331 276	4 933 291	4 331 276

[a] The number of observations is somewhat lower when allowing for virtual income effects. This is mainly because we have conditioned on individual's cohabitation status being unchanged over the period, as spouse's income is included in virtual income. *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

Table A.2 shows the full regression output when categorizing the sample with respect to gender and cohabitation status. In all regressions, we have included a centered third degree polynomial of the base year income as a mean reversion control. The results show relatively little variation with respect to these categorizations.

Table A.2. Estimates of the net-of-tax rate elasticity for earned income. 2SLS regression results by gender and cohabitation status, standard errors in parentheses

	Female, single	Male, single	Female, couple	Male, couple
Net-of-tax rate elasticity	0.0377***	0.0395***	0.0441***	0.0547***
	(0.0061)	(0.0059)	(0.0049)	(0.0031)
Wealth	-0.0002***	0.0001*	-0.0007***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	0.0001	-0.0030***	0.0072***	-0.0016***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Age squared	-0.0000	0.0000***	-0.0000***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married	0.0175***	0.0067***	0.0137***	0.0132***
	(0.0011)	(0.0010)	(0.0005)	(0.0004)
Newborn	-0.1401***	-0.0072	-0.1430***	-0.0134***
	(0.0026)	(0.0040)	(0.0008)	(0.0005)
No. children under 6	0.0386***	-0.0022	0.0374***	0.0063***
	(0.0018)	(0.0026)	(0.0006)	(0.0003)
No. children above 6	0.0150***	0.0126***	0.0094***	0.0037***
	(0.0005)	(0.0008)	(0.0003)	(0.0002)
Non-western origin	-0.0329***	-0.0582***	-0.0273***	-0.0518***
	(0.0019)	(0.0020)	(0.0014)	(0.0009)
Residence in Oslo	0.0077***	-0.0070***	0.0109***	0.0009**
	(0.0006)	(0.0006)	(0.0005)	(0.0003)
Densely populated area	0.0121***	0.0058***	0.0120***	0.0087***
	(0.0009)	(0.0007)	(0.0006)	(0.0004)
Years of education	0.0141***	0.0162***	0.0157***	0.0123***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Field of education	Yes	Yes	Yes	Yes
3 polynomial	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-0.0371***	0.0434***	-0.2217***	0.1141***
	(0.0074)	(0.0071)	(0.0063)	(0.0042)
Number of observations	576 232	959 151	1 109 651	2 287 960

Note: Third degree polynomial of base year income is used as mean reversion control. *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

Robustness checks

In the following we present robustness checks regarding sample restrictions and choice of time span, since the decisions to include individuals above percentile 33 and to use three-year differences are both questionable. In Table A.3, we present results for the net-of-tax rate elasticity for alternative cut-off rules.[26] In the first regression, we include all individuals in percentile 25 or above, and in the third regression we include all individuals in percentile 40 or above. We expect the estimate of the net-of-tax rate elasticity to be independent of this choice, since, irrespective of the cut-off point, individuals in the control group were not affected by the reform. The results uncover that there are very small differences in the estimated net-of-tax rate elasticities with respect to sample restrictions.

Table A.3. Data restriction robustness checks for estimates of the net-of-tax rate elasticity, standard errors in parentheses

	Above percentile 25	Above percentile 33	Above percentile 40
Net-of-tax elasticity	0.0520***	0.0531***	0.0534***
	(0.0023)	(0.0023)	(0.0022)
Number of observations	5 486 168	4 933 291	4 439 785

Note: All regressions include control variables for gender, wealth, age, age squared, married, number of children under and above the age of 6, newborn, residence in Oslo/ densely populated area, non-western origin, years of education, dummies for field of education, income shifting control, year dummies and third degree polynomial of base year income. *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

The three-year span has been proposed in the literature to allow some time for individuals to respond to tax changes. The choice is ad hoc, however, and here we present the results for alternative spans, one to four years. Again, the third degree polynomial is used as the mean reversion control. The results are relatively robust to alternative spans, with the lowest elasticity of 0.032 for one year differences. The likely reason is that wage earners do not respond immediately to tax changes. The elasticity seems to be highest when three-year spans are used.

Table A.4. Robustness checks for time-span assumption for estimates of the net-of-tax rate elasticity, standard errors in parentheses

	One year	Two years	Three years	Four years
Net-of-tax elasticity	0.0320***	0.0418***	0.0531***	0.0463***
	(0.0023)	(0.0022)	(0.0023)	(0.0026)
Number of observations	7 375 466	6 080 466	4 933 291	3 960 093

Note: All regressions include control variables for gender, wealth, age, age squared, married, number of children under and above the age of 6, newborn, residence in Oslo/ densely populated area, non-western origin, years of education, dummies for field of education, income shifting control, year dummies and third degree polynomial of base year income. *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

[26] Tables A.3 and A.4 are based on the same specification as Table A.1 (Specification 5), with third degree polynomials and without virtual income control.

Moreover, we have assessed the extent to which the comparison of results from the structural labor supply model and the ETI panel data approach are influenced by sample differences. The estimation of the labor supply model is based on survey information since it requires detailed information on working hours (see Appendix B), whereas the earnings elasticities presented here are derived from a larger panel data set consisting of the complete set of wage earners. We have therefore looked at the representativity of the observations from the Labor Force Survey (which can be identified through common identification numbers in the panel data set) by limiting the sample to these individuals in an ETI panel estimation. We find that the results for this much smaller sample are not statistically different from the results reported above. However, the estimates are less precise due to the considerable smaller sample size (only about one percent of the wage earner population). The results are available upon request.

Appendix B. Specification and estimation of the discrete choice model

The discrete choice model presented in Section 2.1 is estimated for single females, singles males and for coupled females and males. For persons in couples, we also estimate individual models, but take the income of the spouse into account by including their income as non-labor income.

To simplify the choice, we group jobs into 11 categories based on weekly hours of work: $h_w \in \langle 0-5, 5-10, 10-15, ..., 45-50, 50+ \rangle$. As noted in Section 2, the particular job choice model involves incorporating differences in opportunities into the labor supply modeling, represented by individual differences, θ_i, and variations in opportunities with respect to working hours, $g(h)$. We assume that the densities of offered hours are uniform except for peaks at full-time (35–40), whereas we let the individual differences be determined by years of education (*S*).[27]

The deterministic part of preferences is represented by the following "Box-Cox" type utility function, $v(C,h) = \alpha_0 \frac{(C-C_0)^{\alpha_1}-1}{\alpha_1} + (\beta_0 + \gamma X)\frac{(\bar{h}-h)^{\beta_1}-1}{\beta_1}$, where C measures the household-adjusted consumption level, constructed by dividing the couple or individual's disposable income by $\sqrt{N}$, where N is the number of individuals in the household (including children under 18). C_0 represents the minimum or subsistence household-adjusted consumption level, here set to NOK 60 000. $\bar{h}$ is defined as 80 hours per week and h is working hours per week, so that $(\bar{h}-h)$ measures leisure time. X is a vector of taste-modifying variables including age, education level, children, residence, and origin.

Information about actual and formal working hours in primary and possible secondary jobs and information about labor market status are obtained from the Labor Force Survey of 2004 (Statistics Norway, 2003). This is the main source of labor market statistics in Norway, providing information about approximately 24 000 individuals. Each respondent is asked about hours of work and attachment to the labor market in a reference week over eight consecutive quarters. Information about incomes, family composition, number of children, education, etc. is obtained from the Income Statistics for Persons and Families (Statistics Norway, 2005) and merged with the Labor Force Survey, using unique personal identification numbers. Based on information about labor force status, we have

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[27] θ_i is not identified for males due to the low frequency of non-participation.

included wage earners and "potential" wage earners, coded as employed and home workers. Unemployed, self-employed, disabled persons and students are excluded from the sample. We further limit the sample to persons aged between 25 and 62 years, and we define a person as non-participating if he or she works less than five hours per week.

Working hours are measured as actual hours of work in both the primary and secondary job, using the average of the reference week information for four quarters. It is a key assumption that this average is a good proxy of a "normal" working week during the year. An alternative to this measure of working hours is to use contractual hours of work, but we then loose some of the variation in working hours and introduce a possible measurement error in the calculation of the wage rate. The reason is that individuals who normally work overtime, might be paid for that through their standard wage or have the option of charging employers for their extra workload. We see it as important to account for this characteristic of the labor market, also because we focus on tax changes at high income levels in the present study. If the respondent only participates in the Labor Force Survey in one quarter or if information on actual hours is missing (for example due to illness), contractual hours are used instead. Contractual hours are also used if there is a big difference between contractual and actual hours.

In order to estimate the multinomial logit model,[28] it is necessary to simulate the counterfactual disposable income levels for each discrete alternative, for each individual. Since the Labor Force Survey does not contain any wage information, we compute the hourly wage as yearly wage income (obtained from register-based tax return data) divided by hours per year (measured as 48 times the average weekly hours). The log of computed wage rates is then regressed on individual characteristics using, for females, a Heckman two-stage regression (Heckman, 1979) to account for the selection of individuals not participating (coded as home-working in at least one of the four quarters), while a standard OLS regression is used for males.[29] The number of children and wealth are used as exclusion restrictions under the hypothesis that these variables affect participation, but not wages. Individuals with improbably low or high computed hourly wage rates (under NOK 60 or above NOK 1 200 in 2004) were excluded in the wage regression. For all individuals, we used the predicted wage rate, accounting for a random effect by adding an error term based on draws (30 draws per individual) from a normal distribution.

[28] This type of multinomial logit model with alternative-varying regressors is also called a conditional logit model; see, e.g., McFadden (1984).

[29] The number of home-working males is small.

The actual and counterfactual consumption levels are simulated by multiplying the wage rate by the median point of the discrete intervals. For couples, the income level of the spouse is assumed to be exogenously given and included in non-labor income. As seen in Section 2.1, consumption is modeled as $C = f(hw, I)$, where a tax simulation program is used to simulate taxes and disposable income for each individual's hypothetical working hours choice.

Tables B.1 and B.2 report the results of the wage equation regressions, whereas Tables B.3 and B.4 show the results of the labor supply multinomial logit model. For all four groups we observe positive marginal utility of both consumption and leisure (α_0 and $\beta_0 + \gamma X$ are positive), and α_1 and β_1 are less than 1, which implies that the likelihood functions are strictly concave.

Table B.1. Results of wage regressions for single males and males in couples: log of hourly wage as the dependent variable

	Single males		Males in couples	
	Coefficient	Std error	Coefficient	Std error
Experience	0.0207***	(0.0026)	0.0282***	(0.0023)
Experience squared	-0.0003***	(0.0001)	-0.0005***	(0.0000)
Low education	-0.1150***	(0.0244)	-0.0919***	(0.0169)
High education	0.2379***	(0.0162)	0.2611***	(0.0113)
Residence in densely populated area	0.0864***	(0.0143)	0.1054***	(0.0110)
Non-western origin	-0.1270**	(0.0403)	-0.1395***	(0.0244)
Business code (ref. Public)				
Industry	0.1339***	(0.0182)	0.1561***	(0.0128)
Commerce	0.0130	(0.0192)	0.0827***	(0.0141)
Financial	0.1012***	(0.0218)	0.1556***	(0.0151)
Constant	4.8983***	(0.0305)	4.8425***	(0.0297)
R-square	0.175		0.191	
Number of observations	2 336		4 775	

Note: *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

Table B.2. Results of wage regressions (Heckman two-stage selection model) for single females and females in couples: log of hourly wage as the dependent variable

	Single females		Females in couples	
	Coefficient	Std error	Coefficient	Std error
Experience	0.0173***	(0.0021)	0.0136***	(0.0023)
Experience squared	-0.0003***	(0.0000)	-0.0002***	(0.0000)
Low education	-0.0732***	(0.0217)	-0.0778***	(0.0162)
High education	0.2022***	(0.0133)	0.2071***	(0.0105)
Residence in densely populated area	0.0537***	(0.0121)	0.0650***	(0.0098)
Non-western origin	-0.0409	(0.0390)	-0.0292	(0.0246)
Business code (ref. Public)				
Industry	0.1630***	(0.0207)	0.1127***	(0.0144)
Commerce	-0.0088	(0.0149)	0.0094	(0.0114)
Financial	0.0872***	(0.0176)	0.1196***	(0.0136)
Constant	4.8652***	(0.0257)	4.8982***	(0.0328)
Participation				
Experience	0.0886*	(0.0344)	0.0820***	(0.0170)
Experience squared	-0.0018*	(0.0007)	-0.0018***	(0.0003)
Low education	-0.2047	(0.2290)	-0.2783*	(0.1160)
High education	0.9193***	(0.2679)	0.4748***	(0.0926)
Residence in densely populated area	0.0347	(0.1855)	0.0062	(0.0845)
Non-western origin	-0.9852***	(0.2810)	-0.7655***	(0.1323)
Business code (ref. Public)				
Industry	-0.2066	(0.2490)	0.1786	(0.1322)
Commerce	0.3213	(0.2303)	0.2037*	(0.0991)
Financial	-0.1286	(0.2290)	-0.3698***	(0.0952)
Married			0.0007	(0.0993)
Number of children under 3 years	-0.9486***	(0.2476)	-0.1609	(0.0984)
Number of children under 6 years	-0.1894	(0.2662)	-0.1811	(0.0958)
Number of children under 12 years	-0.2978	(0.1556)	-0.2012***	(0.0594)
Net wealth in NOK 10 000	-0.0033*	(0.0014)	-0.0015*	(0.0008)
Constant	1.4808***	(0.3866)	1.3079***	(0.2374)
Mills lambda	-0.1385*	(0.0620)	-0.2312***	(0.0678)
Observations	2 169		4 771	
Censored observations	45		210	
Wald chi2	454.83		755.75	
Prob<chi2	0.0000		0.0000	

Note: *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

Table B.3. Parameter estimates of the labor supply model, single females and single males

		Single females		Single males	
		Coefficient	Std Error	Coefficient	Std Error
Consumption					
Constant (Scale 10^{-4})	α_0	0.5754***	(0.0736)	0.7975***	(0.1138)
Exponent	α_1	0.8082***	(0.0624)	0.7368***	(0.0540)
Leisure					
Age	γ_1	-0.0243	(0.0311)	-0.0527	(0.0428)
Age Squared	γ_2	0.0005	(0.0004)	0.0008	(0.0005)
High Education	γ_3	-0.1377	(0.0773)	0.0801	(0.1269)
Low Education	γ_4	0.1213	(0.1430)	-0.1073	(0.1818)
# Children under 6 years	γ_5	-0.5097**	(0.1642)	-0.369	(0.4103)
# Children above 6 years	γ_6	-0.1520*	(0.0738)	-0.5175*	(0.2120)
Residence in densely pop area	γ_7	-0.2573**	(0.0831)	0.1216	(0.1157)
Non-western origin	γ_8	0.223	(0.2222)	0.4157	(0.3343)
Constant (Scale 1/80)	B_0	2.1765**	(0.7622)	3.3612**	(1.2892)
Exponent	β_1	-2.4314***	(0.2602)	-1.5869***	(0.3166)
Opportunity measure: $\log(\theta) = f_1 + f_2 S$					
Constant	f_{F1}	-1.1574	(1.0491)		
Years of education	f_{F2}	0.1388	(0.0901)		
Opportunity density of offered hours					
Full-time peak		1.1117***	(0.0547)	1.3801***	(0.0505)
Number of observations		2 208		2 378	

Note: *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

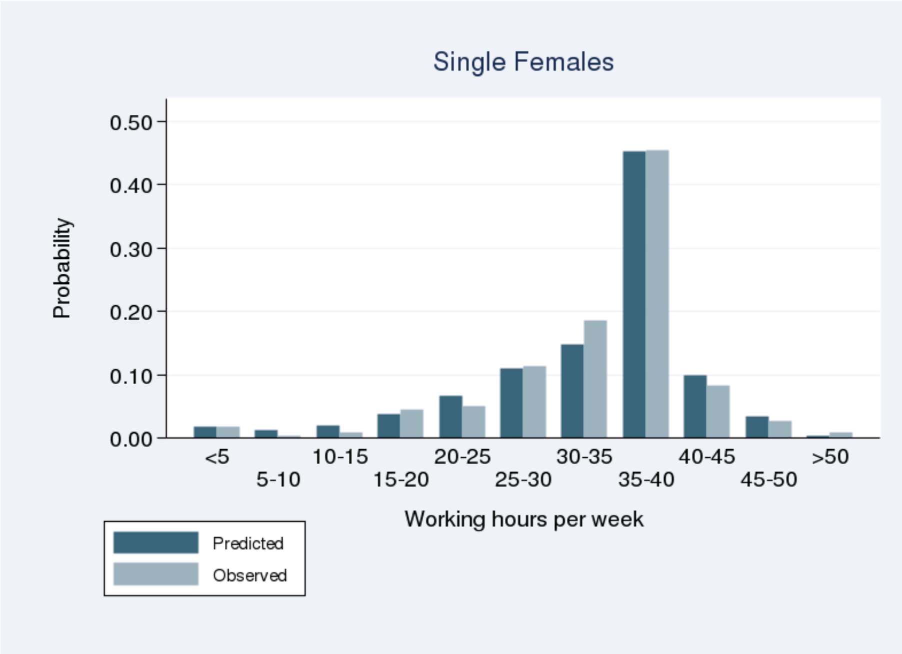
Table B.4. Parameter estimates of the labor supply model, females and males in couples

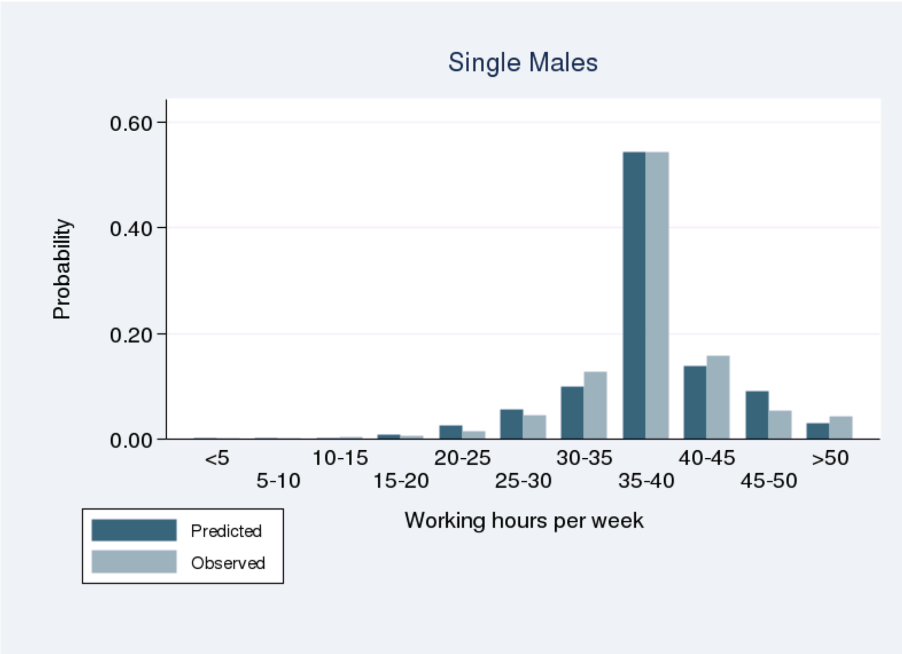
		Females in couples		Males in couples	
		Coefficient	Std Error	Coefficient	Std Error
Consumption					
Constant (Scale 10^{-4})	α_0	0.7534***	(0.0663)	1.4557***	(0.1543)
Exponent	α_1	0.8844***	(0.0281)	0.7682***	(0.0386)
Leisure					
Age	γ_1	-0.0086	(0.0235)	-0.0402	(0.0363)
Age squared	γ_2	0.0004	(0.0003)	0.0007	(0.0004)
High education	γ_3	-0.2178***	(0.0466)	0.2526**	(0.0922)
Low education	γ_4	0.016	(0.0876)	-0.2817*	(0.1154)
# Children under 6 years	γ_5	-0.0314	(0.0443)	-0.1953**	(0.0706)
# Children above 6 years	γ_6	-0.0119	(0.0296)	-0.2574***	(0.0646)
Residence in densely pop	γ_7	-0.2206***	(0.0517)	-0.0295	(0.0730)
Non-western origin	γ_8	0.1354	(0.1117)	0.2702	(0.1739)
Constant (Scale 1/80)	β_0	1.5258**	(0.5155)	3.3593***	(0.8972)
Exponent	β_1	-2.7613***	(0.1503)	-1.7919***	(0.1512)
Opportunity measure $\log(\theta) = f_1 + f_2 S$					
Constant	f_1	-2.8891***	(0.5148)		
Years of education	f_2	0.1946***	(0.0449)		
Opportunity density of offered hours					
Full-time peak		0.9405***	(0.0381)	1.4418***	(0.0355)
Number of Observations		4 841		4 814	

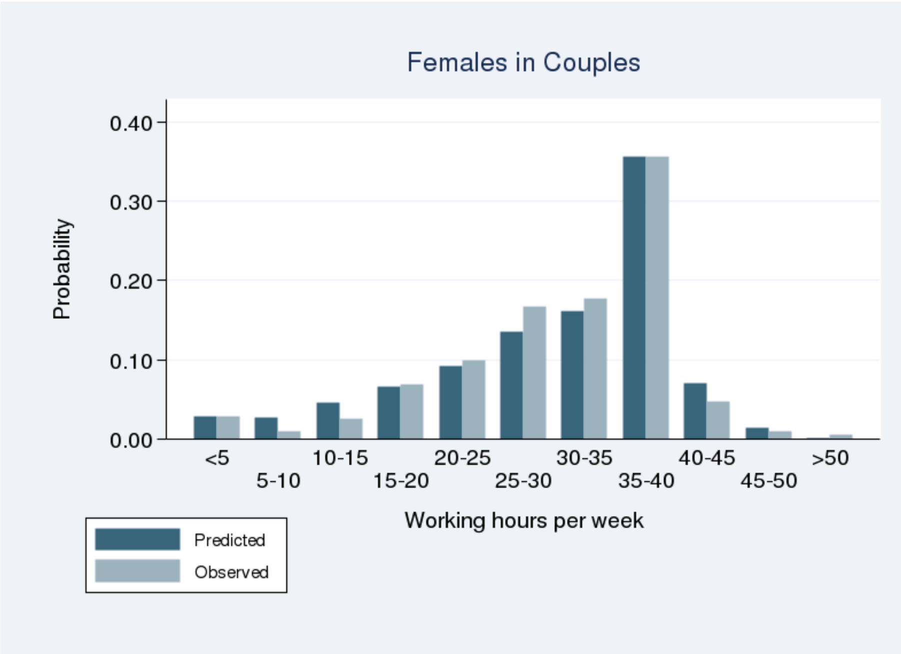
Note: *significant at 0.10 level, ** significant at 0.05 level, ***significant at 0.01 level

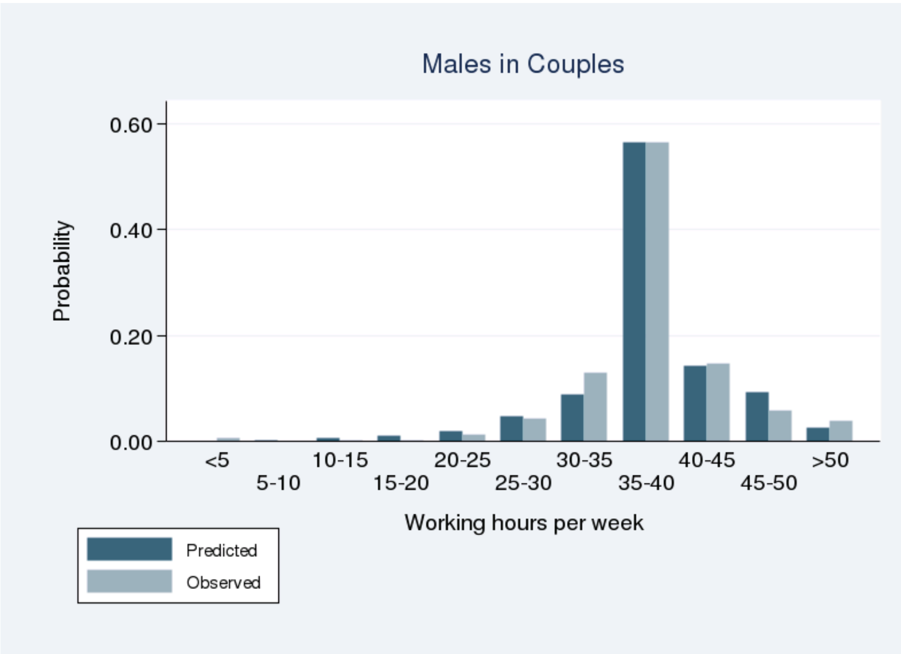
In order to further evaluate the estimation results, Figure B.1 shows diagrams of the actual frequencies of working hours and the corresponding probability distribution based on model simulations, for single females, single males, and females and males in couples. The simulated probabilities are derived by calculating the average probability for each choice of hours, based on the individual probabilities. We see that there is close correspondence between observed and predicted choices.

Figure B.1. Predicted and observed probabilities for working hours






Females in Couples
Probability
0.40
0.30
0.20
0.10
0.00
<5
5-10
10-15
15-20
20-25
25-30
30-35
35-40
40-45
45-50
>50
Working hours per week
Predicted
Observed


Males in Couples
Probability
0.60
0.40
0.20
0.00
<5
5-10
10-15
15-20
20-25
25-30
30-35
35-40
40-45
45-50
>50
Working hours per week
Predicted
Observed

B

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