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# Labour Supply Responses to Tax Reforms in Denmark

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*Labour Supply Responses to Tax Reforms in Denmark*



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# Foreword

This paper is about the effects of income taxes on the number of hours worked in Denmark. While taxes finance government expenditure, taxes may also discourage work, and striking the balance between taxation and expenditure is a perennial topic of political discussion. The extent to which tax incentives affect labour supply is an important input to the policy debate, yet the latest evidence is based on Danish data collected in the 1990's. Since these earlier studies were conducted, the tax system has been reformed a number of times, leading to substantial falls in marginal tax rates, and new and better data has been collected. This paper brings the evidence basis up to date by estimating econometric models on combined survey and administrative data covering the period 1997-2015.

Earlier iterations of this study have benefitted from comments received from Hans Bækgaard, Carl-Johan Dalgaard, Lars Gårn Hansen, John Smidt, Michael Svarer, Torben Tranæs and David Tønners. Nevertheless, all remaining errors are those of the author alone.

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*Hans Hummelgaard*
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# Contents

# Introduction

Taxation affects work effort and causes inefficiencies because taxes change incentives to work and effort responds to these incentives. To inform the design of tax policy we need to know how effort responds to tax incentives. Effort can adjust along several margins – hours worked over different time periods, effort expended per hour, earnings from work versus income from capital – and different margins might be relevant for different groups. For the self-employed or the highly skilled who are already working long hours, the relevant margin might be working harder or greater concentration, and modelling gross income responses to tax changes might be appropriate, However, for many people, hours of work is a good measure of effort, and modelling of hours responses to tax changes is more appropriate. In this study we model hours of work responses.

There is an extensive literature measuring the response of effort to tax incentives. In the next section, we describe the theoretical basis and the empirical challenges facing labour supply modelling, with a view to motivating our own empirical strategy in Section 2. For reviews of the literature, see Blundell, MaCurdy and Meghir (2007) and Meghir and Phillips (2010) on structural life-cycle consistent models; Keane (2011) on structural dynamic models; Saez, Slemrod and Giertz (2012) on reduced form models. Our first contribution is estimating a labour supply model for Denmark which is consistent with life-cycle behaviour.

In Section 3 we describe the Labour Force Survey and administrative data we use. We combine survey responses about actual hours worked with administrative data allowing precise calculation of marginal tax rates. This combination covers 1997-2015; a period spanning several tax reforms, providing variation that helps identifying labour supply models. Our second contribution is an analysis including recent data and recent reforms that have not previously been analysed.

In Section 4 we present our results in terms of estimated coefficients and uncompensated wage elasticities. By virtue of our large sample we are able to split the data to examine how behaviour varies across different groups. Our third contribution is the analysis of heterogeneity between subsamples; heterogeneity that has not been a feature of previous Danish studies. We conclude with a summary of our findings, placing them alongside previous Danish labour supply studies. These findings have caveats and we recall the assumptions they are based on. Finally, we discuss the prospects for future works modelling dynamics and increasing precision.

# 1 Labour Supply Modelling

## 1.1 Static models

Labour supply models consider the trade-off between hours of work and leisure by making assumptions about preferences and assuming hours worked are a function of the after-tax marginal wage rate, non-labour (virtual) income and background characteristics related to tastes for work, e.g. marital status, ages of children, and level of schooling. In the first instance, consider a single time period: Compared to a system with no taxes, introducing a proportional tax would lead to a reduction in hours of work at low hours, but may increase hours of work from high hours if the income effect dominates the substitution effect.

Introducing progressive taxes with higher tax rates over bands of higher income, behaviour within each tax band can be thought of as behaviour within a proportional system, with higher bands featuring higher marginal tax rates and higher virtual income. Progressive taxes give rise to a convex budget constraint, and hours of work responses to tax changes depend upon the responsiveness of individuals to marginal tax rates and to virtual income, and where individuals are distributed along the budget constraint relative to where the tax rates change.

## 1.2 Inter-temporal models

Simple labour supply studies are static, and introducing life-cycle dynamics requires also modelling savings decisions; or at the very least, accounting for inter-temporal allocation when modelling labour supply. Assuming that preferences are separable over time – that past behaviour doesn't affect current preferences or constraints – implies that preferences in the current period are only a function of current leisure and consumption. Separability of preferences allows the inter-temporal allocation problem to be unbundled from the within-period labour supply decision; it allows for two-stage budgeting, where individuals allocate consumption between time periods and then decide on labour supply (Gorman, 1959).

The practical implication of separable preferences allowing two stage budgeting is that, in a sense, the static labour supply model prevails, but with non-labour income re-defined; rather than within period virtual income, the relevant non-labour income concept becomes consumption minus net earnings. So, while the within-period decision problem can be thought of as the same as in the static case, when unearned income depends upon consumption, current and future taxes become relevant for savings decisions in order to know current period consumption. In the case of progressive taxes with a convex budget constraint, consumption data is required to compute unearned income for estimating a labour supply model which is consistent with intertemporal optimization (Blundell and Walker, 1986).

## 1.3 Labour market programmes

Progressive taxes and convex budget constraints are convenient for labour supply modelling because along budget constraint segments optimum hours of work can be shown to continuously adjust to tax rate changes, allowing marginal analysis of local responses. However, in the presence of labour market programmes and welfare transfers, the marginal net wage rate changes as subsidies are withdrawn, leading to non-convexities in the budget constraint. With non-convexities, small changes in tax rates can lead to potentially large changes in labour supply, invalidating the modelling of marginal analysis of local responses.

As an alternative to modelling continuous hours, discrete choice modelling avoids the pitfalls of considering marginal responses. Behaviour is assumed to be a choice between a limited set of hours possibilities, characterized by a subset of points on the budget constraint, for example non-work, part-time work and full-time work. In the presence of budget constraint non-convexities, while discrete choice modelling offers a tractable solution in a static world, allowing for intertemporal substitution becomes much more complex because it requires simulating the effects of taxation on savings in order to recover a measure of non-labour income within-period. In an important sense, a discrete choice model which is simply consistent with inter-temporal behaviour is insufficient, and a dynamic discrete choice model is required to recover behavioural (structural) parameters (French, 2005).

## 1.4 Linearizing the budget constraint

The complexities of estimating dynamic life cycle models motivates revisiting the more tractable models of continuous hours substitution which are life-cycle consistent in the absence of non-convexities. Indeed, for most of the working population, most of the budget constraint is convex, making this special case perhaps the most important. Nevertheless, a couple of practical issues remain to be addressed before implementing the continuous model: kink points between linear segments of the progressive tax schedule, and the work decision.

In the example of a progressive tax schedule with several bands, responses to tax changes can be decomposed into income and substitution effects shifting optimal hours along (within) a given tax band. However, because there are kinks in the budget constraint where the tax rate changes between tax bands, we would expect workers to gather at kink points because responses to tax rate changes would no longer be smooth. When increasing hours from below the kink point they would shift to above the kink point if taxes continued at the lower rate (rather than increasing), whereas when decreasing hours from above the kink point they would shift to below the kink point if taxes continued at the higher rate (rather than decreasing) (Gourieroux, Laffont and Montfort, 1980).

Apart from smooth adjustment along linear schedules becoming sticky towards the end of each band, at kink points between bands of the tax schedule, marginal tax rates are not well defined, or rather, they are bracketed from above and below, suggesting stickiness for small tax rate changes for those initially located at a kink. Accommodating differential responses at kinks and along linear segments of the tax schedule, a static structural model of labour supply can be estimated, though this may not be consistent with inter-temporal behaviour (Burtless and Hausman, 1978).

An alternative structural approach which is consistent with inter-temporal behaviour in the presence of progressive taxation is linearization of the budget constraint, whereby continuous hours substitution is modelled within tax bands, while abstracting from sticky adjustments at kink points. This linearization is achieved by dropping observations for individuals working close to a kink point, and adjusting estimates based on the remaining sample for the associated selection. In a similar way, non-workers can be dropped to avoid modelling the participation decision; modelling labour supply conditional on working and adjusting estimates for sample selection (Blundell, Duncan and Meghir, 1998).

## 1.5 Gross income responsiveness

While the forgoing discussion about hours of work responses to changes in taxation might be relevant for much of the population, a large number of high earners and the self-employed may already be working long hours and the relevant margin of response to tax changes might instead be working harder per hour. Hours responses would miss this change, and effort per hour is difficult to measure, leading researchers to consider effects of taxes on taxable income or gross income (Feldstein, 1995).

Apart from taxable income responses obviously being relevant for government revenue, taxable income changes also reflect welfare losses due to individual shifting between income sources in response to differential tax incentives, for example between labour and capital income, or between housing expenditure and other consumption. See Kleven and Schultz (2014) for an excellent application of taxable income response modelling to Danish data. The principal downside of modelling gross income responsiveness is the lack of a structural interpretation because effort is unobserved – paradoxically the motivation for following this approach in the first place. Because effort cannot be measured, we cannot calculate the price of effort, and need to assume that the price of effort does not change differentially between skill groups (Saez, Slemrod and Giertz, 2012).

## 1.6 Our modelling approach

To inform tax policy design we need to know how effort responds to incentives. We can learn how hours of work and taxable incomes have responded to historical tax rate changes by following reduced form approaches describing variations in the data. However, in order to inform policy on the basis of historical behaviour, economists need to estimate structural models and retrieve behavioural parameters for conducting counterfactual simulations.

Modelling taxable income circumvents problems of effort measurement for high earners, but in so doing loses any structural interpretation. Estimation of taxable income responses can proceed by analogy to labour supply modelling by including marginal tax rates and virtual income, but without effort prices, any interpretation remains reduced form. While modelling labour supply may not be relevant for high earners, a modelling approach which linearizes the budget constraint in a way that is life-cycle consistent has a structural interpretation and is relevant for most of the working population.

In view of the aforementioned considerations, we propose a life-cycle consistent labour supply modelling approach which linearizes the budget constraint. Specifically, we model hours worked during a week as a function of net wages and non-labour income. For life-cycle consistency, the non-labour income measure is be derived from consumption minus net earnings; consumption is imputed from administrative data on wealth changes and annual income (Browning and Leth-Petersen, 2003).

## 1.7 Our empirical approach

Having decided which model of effort and incentives best strikes the balance between theoretical consistency and tractability for a large share of the population – a life-cycle consistent model of labour supply – we can now take this model to the data. The main empirical challenge is resolving the direction of causality between incentives and effort. When estimating the effect of incentives on hours of work an endogeneity problem may lead to biased Ordinary Least Squares (OLS) estimates; indeed, the sign of the bias is unknown.

Estimation of static labour supply models has long dealt with the endogeneity of marginal tax rates and virtual income by accounting for preferences in the structural model and imposing functional form restrictions (Hausman, 1985). See Frederiksen and co-authors (2008) for an excellent application of the Hausman model and extension to Danish data. However, two issues remain to be addressed in the Hausman framework: endogeneity of gross, rather than net, wages; imposing theoretical consistency throughout the budget constraint across the population is a strong restriction. Both issues may lead to upward biased estimates of incentive effects (MaCurdy, Green and Paarsch, 1990).

In estimating a life-cycle consistent labour supply model, Blundell, Duncan and Meghir (1998) avoid the two issues which have plagued estimation of static labour supply models. Firstly, by using UK data during a period of changes in the gross wage structure and spanning several tax reforms, they have a source of plausibly exogenous changes in gross and net wages, providing candidate instrumental variables. Secondly, by linearizing the budget constraint, theoretical consistency need not be imposed at kinks in the budget constraint – the origin of the bias highlighted by MaCurdy and co-authors. Operationalizing the solutions to both problems require making auxiliary assumptions which are worth emphasizing.

To exploit changes in the gross wage structure, individuals are assigned to groups according to birth cohort and education level. Mean gross wages for these groups changes differentially over time, and while preferences for work may differ between groups, the maintained assumption is that preferences do not change between groups. In other words, labour supply changes can be attributed to gross wage changes rather than changes in preferences. With the addition of tax reforms which affect different groups differently, assuming that tax incidence doesn't completely offset the reforms, the net wage elasticity can be identified. These assumptions motivate a generalized Wald estimator or grouped instrumental variables estimator (Heckman and Robb, 1985).

In linearizing the budget constraint, labour supply is modelled conditional on working positive hours and being on convex sections of the budget constraint away from kink points; to be representative of the population, estimates need to be corrected for this sample selection. In the grouped estimator framework, assuming linear conditional expectations allows for correction for selection into work by way of inclusion of an inverse Mill's ratio, corresponding to the proportion of each group in each time period with positive hours (Heckman, 1974). An additional assumption is, of course, that some differential changes in gross wages between-groups remains after correcting for selection.

Analogously to correction for selection into work, estimators linearizing the budget constraint can also correct for selection away from kink points. A similar assumption of linear conditional expectations allows for inclusion of another inverse Mill's ratio term, this time from a model of grouping at kinks of the budget constraint. Identification of these (two) additional parameters for selection correction require additional instruments from other tax reforms (Blundell, Reed and Stoker, 1993), or functional form restrictions (Blundell, Duncan and Meghir, 1998).

In view of the aforementioned considerations, we propose a grouped instrumental variables empirical approach. We use changes in the gross wage structure across education levels and cohorts over time, appealing to evidence of skill-biased technical change in Denmark (Malchow-Møller and Skaksen, 2004). Furthermore, we characterize tax reforms by constructing budget constraints at several pre-determined levels of gross earnings.

# 2 The Model

We adopt a semi-log labour supply function, following Blundell, Duncan and Meghir (1998). This function has several attractive properties: Allowing non-linear curvature in wage effects while remaining linear in income; log-linearity in wages allows proportional taxes to enter linearly. See Blundell and MaCurdy (1999) for a comparison with other popular labour supply functions, and Stern (1986) for the implied direct and indirect utility functions. Our labour supply function is as follows:

(1) $h_{it} = \alpha_i + \gamma_t + \theta^h X_{it} + \beta \ln(1-\tau)_{it} + \gamma\mu_{it} + \varepsilon_{it}^h$

Where $h_{it}$ is actual hours worked in survey week $t$ by individual $i$. $\alpha_i$ is a dummy variable for each individual, $\gamma_t$ is a dummy variable for survey week (dummies for each week number and dummies for each calendar year), $X_{it}$ is a set of demographic characteristics ($\theta$ is an associated coefficient), $\tau$ is the marginal tax rate for additional labour income ($\beta$ is an associated coefficient) ), $\mu_{it}$ is other income to be defined below ($\gamma$ is an associated coefficient), $\varepsilon_{it}^h$ is an error term.

The set of demographic characteristics are binary indicators for married, male, any children in age ranges 0-2, 3-6, 7-9, 10-14, 15-17, education less than high school (10<*hffsp*<19), college graduate (40<*hffsp*<90) (high school education is the reference group), high urbanicity (*degurb*=1), low urbanicity (*degurb*=3) (medium urbanicity is the reference group), and age dummies. Other income is defined so as to be consistent with intertemporal two-stage budgeting (Blundell and Walker, 1986). First define saving as the difference between wealth (*formrest_ny05*) in two periods. Second define the average tax rate (*atr*) as tax paid (*skattot_13* + *slutbid* + *kiskat*) divided by total income (*totalinc = perindkp* + *slutbid* + *kapindk* + *aktieindk* + *korstoett* + *korydial*). Finally, given that we know labour *earnings* (*loenmv_13*) and can calculate individual marginal tax rates $\tau_i$, we calculate other income as totalinc*(1-atr)-earnings*(1- $\tau_i$)-saving.

Because the individual marginal tax rate $\tau$ and individual other income $\mu_{it}$ are endogenous (depend upon hours worked), we need to instrument for $\tau$ and $\mu_{it}$ with features of the tax system that are not dependent upon hours of work. Following Blundell, Duncan and Meghir (1998) we calculate grouping instruments for other income, arguing that variation in other income according to birth cohort and schooling level has evolved exogenously over time. Specifically, we calculate medians of other income by groups according to the interaction of cohorts (1940-49, 1950-59, 1960-69, 1970-79, 1980-89), schooling (below, at, or above high school level), and for each calendar year. For individual marginal tax rates we instrument by marginal taxes at several pre-defined levels of earnings on the individual budget constraint – from 100,000 up to 500,000 kr. gross earnings in increments of 100,000 kr.

Instrumentation takes the form of the following two first stage regressions:

(2) $\ln(1-\tau)_{it} = \Sigma\delta^{\tau}_{E}\ln(1-\tau_E)_{it} + \zeta^{\tau}\mu_{G(it)} + \theta^{\tau}X_{it} + \varepsilon_{it}^{\tau}$

(3) $\mu_{it} = \Sigma\delta^{\mu}_{E}\ln(1-\tau_E)_{it} + \zeta^{\mu}\mu_{G(it)} + \theta^{\mu}X_{it} + \varepsilon_{it}^{\mu}$

W here $(1-\tau_E)_{it}$ is one minus the marginal tax rate at hypothetical earnings level $E$ for individual $i$ in time period $t$ ($\delta^{\tau}_{E}$ is the associated coefficient in the first stage for the marginal tax rate and $\delta^{\mu}_{E}$ is the associated coefficient in the first stage for other income), $\mu_{G(it)}$ is median other income for cohort-schooling-year group $G$ to which individual $i$ belongs in time period $t$ ($\zeta^{\tau}$ is the associated coefficient in the first stage for the marginal tax rate and $\zeta^{\mu}$ is the associated coefficient in the first stage for other income).

The labour supply function is conditional on positive hours of work and conditional on not being close to a kink in the budget constraint, hence observations with zero hours or within kink-proximity are dropped from the main analysis and estimates need to be adjusted to account for this sample selection. We estimate two reduced form probit functions to explain the sample selection:

(4) $P_{it} = \Sigma\delta^{P}{}_{E}\ln(1\text{-}\tau_{E})_{it} + \zeta^{P}\mu_{G(it)} + \theta^{P}X_{it} + \varepsilon_{it}{}^{P}$

(5) $K_{it} = \Sigma\delta^{K}{}_{E}\ln(1\text{-}\tau_{E})_{it} + \zeta^{K}\mu_{G(it)} + \theta^{K}X_{it} + \varepsilon_{it}{}^{K}$

Where $P_{it}$ takes the value one if $h_{it}>0$, and takes the value of zero otherwise; $K_{it}$ takes the value one if individual *i* in time period *t* is observed away from a kink point, and takes the value zero otherwise.

We can re-write our original labour supply function (1), now taking into account the endogeneity of marginal tax rates and other income, and accounting for sample selection into work and away from a kink point in the budget set:

(6) $h_{it} = \alpha_{i}{}^{*} + \gamma_{t}{}^{*} + \theta^{h*}X_{it} + \beta^{*}[\ln(1\text{-}\tau)_{it}]^{*} + \gamma^{*}[\mu_{it}]^{*} + \rho^{P}\lambda_{it}{}^{P} + \rho^{K}\lambda_{it}{}^{K} + \varepsilon_{it}{}^{h*}$

Where $[\ln(1\text{-}\tau)_{it}]^{*}$ is the instrumented value of $\ln(1\text{-}\tau)_{it}$ and $\beta^{*}$ is the associated *now unbiased* coefficient, $[\mu_{it}]^{*}$ is the instrumented value of $\mu_{it}$ and $\gamma^{*}$ is the associated *now unbiased* coefficient, $\lambda_{it}{}^{P}$ is an Inverse Mills Ratio from participation equation 4 ($\rho^{P}$ is an associated coefficient), $\lambda_{it}{}^{K}$ is an Inverse Mills Ratio from kink-proximity equation 5 ($\rho^{K}$ is an associated coefficient).

Equation 4 is estimated on the gross sample, equation 5 is estimated for the sample with positive hours, equations 2, 3 and 6 are estimated on the sample with positive hours and not close to a kink.

# 3 The Data

We use the Labour Force Survey which is conducted by Statistics Denmark on behalf of Eurostat. The survey has been run throughout each year since 1994, and we link administrative data to surveyed individuals over the period 1997-2015. Before 2007, the sampling frame was such that 0.5 percent of the population were interviewed three times; with about 13 weeks between the first and second interviews and about 52 weeks between the second and third interviews; corresponding to quarters 1, 2 and 6. From 2007, the sample size was doubled to 1.0% of the population, now with each person interviewed four times at intervals 13, 39 and 13 weeks; corresponding to quarters 1, 2, 5 and 6. We use sampling weights to make our inference representative of the population in a consistent way throughout the period.

The main reason for using the Labour Force Survey is because of the question about actual hours worked which is asked consistently throughout such a long period. While recent administrative data has broader coverage, it does not span the historical reforms to the tax system which help to identify our models. We link administrative data about demographics and income, and courtesy of the Finance Ministry tax simulator are able to calculate budget constraints and marginal tax rates for almost all observations.

**Table 3.1** Descriptive statistics for the estimation sample

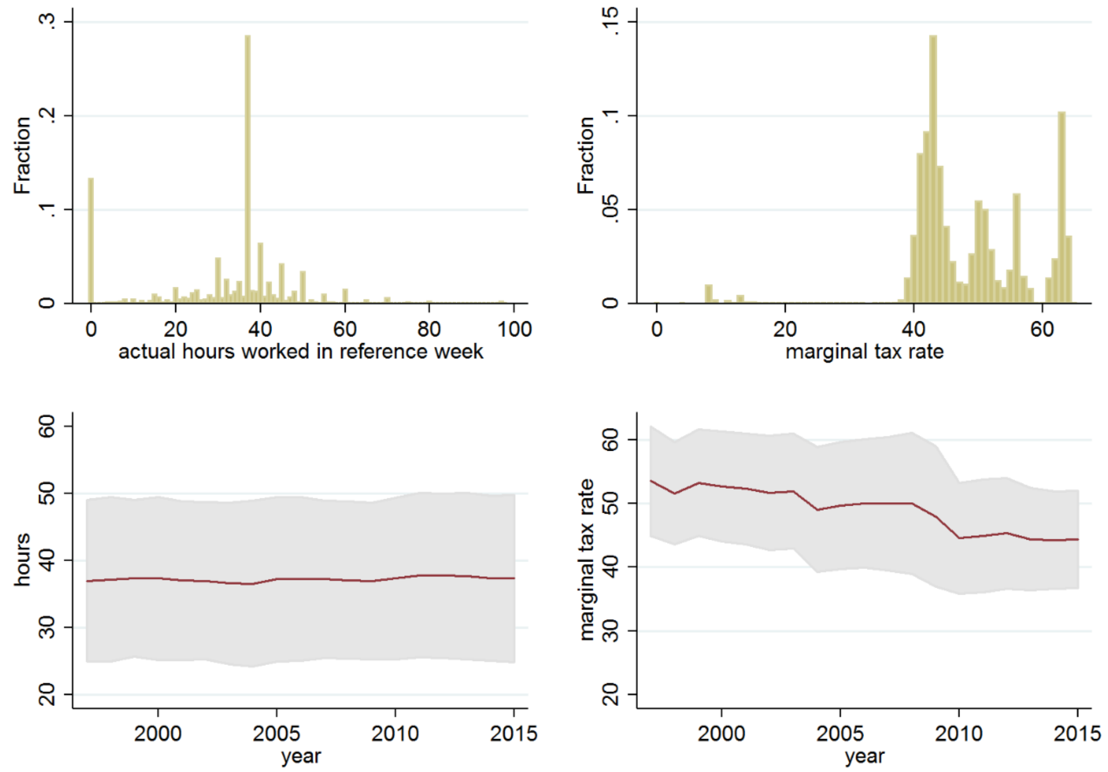
| | original | | max oi | | h>0 | | no kink | | final | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | | (5) | |
| hours | 32.593 | *17.167* | 32.484 | *17.088* | 37.472 | *12.245* | 37.447 | *12.314* | 37.665 | *12.111* |
| male | 0.5223 | | 0.5200 | | 0.5350 | | 0.5350 | | 0.5381 | |
| married | 0.6183 | | 0.6175 | | 0.6174 | | 0.6166 | | 0.6287 | |
| children 0-2 | 0.1266 | | 0.1266 | | 0.1119 | | 0.1122 | | 0.1086 | |
| children 3-6 | 0.1709 | | 0.1709 | | 0.1663 | | 0.1665 | | 0.1672 | |
| children 7-9 | 0.1396 | | 0.1394 | | 0.1389 | | 0.1390 | | 0.1416 | |
| children 10-14 | 0.1971 | | 0.1965 | | 0.1991 | | 0.1988 | | 0.2040 | |
| children 15-17 | 0.1242 | | 0.1237 | | 0.1261 | | 0.1260 | | 0.1305 | |
| high school | 0.4642 | | 0.4646 | | 0.4680 | | 0.4678 | | 0.4689 | |
| college | 0.3441 | | 0.3431 | | 0.3381 | | 0.3371 | | 0.3424 | |
| semi-urban | 0.2753 | | 0.2755 | | 0.2753 | | 0.2747 | | 0.2760 | |
| rural | 0.3853 | | 0.3845 | | 0.3863 | | 0.3855 | | 0.3899 | |
| log(1-τ) | -0.6939 | *0.1954* | -0.6945 | *0.1937* | -0.6970 | *0.1952* | -0.6955 | *0.1960* | -0.6984 | *0.1960* |
| μ | 0.0191 | *1.0447* | 0.0232 | *0.2834* | 0.0222 | *0.2856* | 0.0231 | *0.2857* | 0.0230 | *0.2845* |
| log(1-τ) E100k | -0.4169 | *0.2364* | -0.4167 | *0.2354* | -0.4146 | *0.2369* | -0.4153 | *0.2372* | -0.4066 | *0.2384* |
| log(1-τ) E200k | -0.5969 | *0.1451* | -0.5971 | *0.1430* | -0.5967 | *0.1436* | -0.5966 | *0.1445* | -0.5922 | *0.1426* |
| log(1-τ) E300k | -0.7132 | *0.2025* | -0.7135 | *0.2015* | -0.7121 | *0.2011* | -0.7106 | *0.2016* | -0.7019 | *0.1991* |
| log(1-τ) E400k | -0.8681 | *0.1922* | -0.8687 | *0.1911* | -0.8677 | *0.1919* | -0.8647 | *0.1931* | -0.8577 | *0.1958* |
| log(1-τ) E500k | -0.9348 | *0.1025* | -0.9355 | *0.1000* | -0.9352 | *0.1006* | -0.9337 | *0.1013* | -0.9307 | *0.1021* |
| Observations | 612639 | | 607115 | | 525938 | | 490809 | | 420640 | |

Note: Means and *standard deviations in italics*. The five column headers correspond to different samples. *Original* refers to all Labour Force Survey observations fitting our selection criteria without missing variables; *max-oi* removes observations of other income outside the 2,000,000 kr. interval; *h>0* further removes zero hours observations; *no-kink* further removes observations within 5,000 kr. of a 5% kink in the budget constraint; *final* further removes individuals with fewer than two positive hours observations. Data comes from a linkage of the Labour Force Survey and Administrative Registers. From the Labour Force Survey for the reference week: hours are the sum of actual hours in main job (hwactual) and secondary job (hwactual2); *married* is marital status (marstat=2); urbanicity of place of residence with *semi-urban* (degurba=2), *rural* (degurba=3) and reference group urban (degurba=1). From administrative registers the census point is 1 January during the reference year: *Children* are indicator variables for any children in the given age range; education is the highest completed grouped into *college* graduate (40<hffsp<93), *high school* graduate (20<hffsp<39) and reference group less than high school (10<=hssfp<=19). Finally, on the basis of administrative data and courtesy of the Finance Ministry tax calculator, we have calculated individual marginal tax rates $\tau$ and marginal tax rates at 100,000 kr. earnings intervals along individual budget constraints. Other income $\mu$ is calculated as described in the main text. Statistics are weighted using Labour Force Survey weights (coefqq, factor, faktorq) to make them population-representative.

Table 3.1 presents descriptive statistics, beginning with our gross sample in column (1) and ending with our hours estimation sample in column (5). The gross sample is defined as linked Labour Force Survey and administrative data for individuals aged 25-59, with non-missing values for all variables listed in Table 3.1, and with sufficient information for calculating a budget constraint and marginal tax rates. The only sample restriction we make before estimation is removal of observations with extreme values for other income, with absolute value greater than 2,000,000, i.e. 0.9 percent of observations.

Descriptive statistics for the remaining sample are presented in column (2), and this sample is used for estimating equation (4) for positive hours. Column (3) presents descriptive statistics for the sample with positive hours which is used in estimating equation (3) for selection away from a kink on the budget constraint. Column (5) presents the sample with positive hours located away from a kink. To estimate equation (6) with individual fixed effects we need at least two observations for each person, and this final hours estimation sample is described in column (5). While the hours estimation sample is 69 percent of the original sample size, descriptive statistics are remarkably stable throughout the sample selection.

**Figure 3.1** Hours and marginal tax rates




Note: Hours and marginal tax rate distributions from the gross sample. Histograms in the upper panes show fractions in unit cells, i.e., single hour of work and one percent tax. Graphs in the lower panes show means by year (red line) and standard deviations by year (grey shaded area).

Figure 3.1 presents distributions of our outcome of interest – actual hours worked in the reference week – and our main endogenous variable – marginal tax rates. The hours distribution has pronounced modes at 37 and zero, with a modest spread between 20 and 60, and mean hours do not change over the sample period. Marginal tax rates have modes at 43, 50, 56 and 63 percent, spanning the 39-64 percent range, and mean rates have fallen from 53 to 44 percent over the sample period.

# 4 Results

In this Section we present first stage regressions and second stage Instrumental Variables (IV) regressions based on the full sample meeting our selection criteria. We proceed by looking for heterogeneity in estimates between different sub-samples, and complete the Section with some robustness checks examining the sensitivity of estimates to some modelling assumptions.

## 4.1 First stage regressions

The labour supply function we want to estimate in equation (6) differs from our initial labour supply function in equation (1) because we account for endogeneity – of marginal tax rates in equation (2) and of other income in equation (3) – and we account for sample selection – with positive hours in equation (4) and away from budget constraint kinks in equation (5). Estimates from these four first stage regressions are presented in Table 4.1.

**Table 4.1** First stage regression estimates

| | P | | K | | μ | | log(1-τ) | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | |
| log(1-τ) E100k | 0.0957 | *0.0147* | 0.2232 | *0.0209* | -0.0556 | *0.0239* | 1.3681 | *0.0761* |
| log(1-τ) E200k | -0.1095 | *0.0301* | 0.2868 | *0.0408* | 0.0425 | *0.0059* | -0.0530 | *0.0172* |
| log(1-τ) E300k | 0.4498 | *0.0291* | 0.2701 | *0.0388* | 0.1971 | *0.0097* | -0.0705 | *0.0278* |
| log(1-τ) E400k | 0.3463 | *0.0365* | -0.1497 | *0.0555* | 0.0916 | *0.0085* | -0.1288 | *0.0240* |
| log(1-τ) E500k | -0.1193 | *0.0577* | -0.6812 | *0.0878* | 0.0961 | *0.0076* | -0.0697 | *0.0225* |
| $\mu_G$ | 0.1076 | *0.1349* | 0.6641 | *0.2076* | 0.1370 | *0.0180* | -0.1176 | *0.0540* |
| married | -0.0061 | *0.0064* | -0.0148 | *0.0094* | 0.0045 | *0.0027* | 0.0262 | *0.0079* |
| male | 0.2632 | *0.0055* | 0.0021 | *0.0079* | | | | |
| children 0-2 | -0.4825 | *0.0088* | -0.0180 | *0.0143* | 0.0022 | *0.0025* | -0.0055 | *0.0078* |
| children 3-6 | -0.0028 | *0.0083* | -0.0233 | *0.0123* | 0.0004 | *0.0021* | 0.0012 | *0.0057* |
| children 7-9 | -0.0139 | *0.0086* | -0.0184 | *0.0126* | 0.0027 | *0.0018* | -0.0052 | *0.0053* |
| children 10-14 | 0.0056 | *0.0076* | -0.0081 | *0.0110* | 0.0024 | *0.0018* | -0.0071 | *0.0054* |
| children 15-17 | 0.0181 | *0.0085* | -0.0091 | *0.0121* | -0.0008 | *0.0016* | 0.0058 | *0.0047* |
| high school | 0.0193 | *0.0080* | 0.0662 | *0.0115* | -0.0029 | *0.0074* | -0.0266 | *0.0189* |
| college | -0.0272 | *0.0083* | 0.1033 | *0.0121* | -0.0236 | *0.0090* | -0.0364 | *0.0210* |
| semi-urban | 0.0102 | *0.0071* | 0.0287 | *0.0103* | 0.0010 | *0.0030* | 0.0028 | *0.0102* |
| rural | 0.0269 | *0.0067* | 0.0447 | *0.0097* | 0.0056 | *0.0035* | -0.0084 | *0.0110* |
| $\lambda_P$ | | | | | 0.0137 | *0.0080* | -0.0037 | *0.0246* |
| $\lambda_K$ | | | | | 0.6062 | *0.0993* | -0.4762 | *0.2896* |
| Obs./$R^2$ | 607115 | *0.1274* | 525938 | *0.0204* | 420640 | | 420640 | |

Note: Model estimates and *standard errors in italics*. Each pair of columns presents estimates from separate regressions. The column headed P presents probit coefficients estimated on the gross sample where the dependent variable takes the value of one if actual hours are positive and takes the value zero otherwise. The column headed K presents probit coefficients estimated on the positive hours sample where the dependent variable takes the value of one if an observation is close to a kink in the budget constraint (within 5,000 kr. of a 5 percent tax rate change) and takes the value zero otherwise. The column headed μ presents OLS coefficients estimated on the sample with positive hours away from a kink where the dependent variable is other income. The column headed log(1-τ) presents OLS coefficients estimated on the sample with positive hours away from a kink where the dependent variable is the log of one minus the marginal tax rate on earnings. Variable μG is median other income for the schooling-cohort-year group, λP is an inverse Mill's ratio from the probit estimated in column P, λK is an inverse Mill's ratio from the probit estimated in column K. All regressions are run using Labour Force Survey weights (coefqq, factor, faktorq) to make them population-representative.

Probit coefficients are presented in columns (1) and (2). OLS coefficients are presented in columns (3) and (4). The sets of explanatory variables are the same across the equations, with two exceptions. Firstly, OLS estimates include individual fixed effects ($\alpha_i$), whereas probit estimates do not. A corollary of this difference is that we control for gender in the probit regressions, but gender control is redundant for OLS because of fixed effects. Secondly, OLS estimates include inverse Mill's ratios ($\lambda_P$ and $\lambda_K$) generated from the probit regressions in order to control for sample selection.

Coefficients in the upper six rows are for excluded instruments – the set of variables we assume only affects hours of work via these first stage regressions, and are thereby legitimately excluded from directly entering the second stage regression. Importantly, excluded instruments are almost always significant. Inverse Mill's ratios for positive hours (selection away from kink) are insignificant (significant) explanatories of other income and marginal tax rates. The sign of the kink selection terms suggests that (unobserved characteristics associated with) kink proximity are positively correlated with (unobserved characteristics associated with) unearned income, but negatively correlated with (unobserved characteristics associated with) net wage rates.

## 4.2 Main Instrumental Variables Estimates

Our instrumental variables adjust for endogeneity of marginal tax rates and other income. Including inverse Mill's ratios adjusts for sample selection into positive hours and away from budget constraint kinks. Table 4.2 presents estimates of interest from IV regressions with and without corrections for selection. While correction only for non-participation slightly increases wage elasticities, correction only for kink proximity slightly decreases wage elasticities; correction for both sources of selection together gives wage elasticities quite similar to those without any correction. Wage elasticities are not significantly different from each other. Coefficients on other income are imprecisely estimated for all specifications.

**Table 4.2** Instrumental Variables estimates accounting for selection

| | No correction | P correction | K correction | P & K correction |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| β | 4.4565 | 5.2489 | 2.9277 | 3.6421 |
| | *1.6192* | *1.6425* | *1.6312* | *1.6466* |
| γ | 0.0159 | -0.1113 | -0.6305 | -0.9293 |
| | *1.0691* | *1.0713* | *1.0823* | *1.0869* |
| $\rho^P$ | × | 2.6362 | × | 3.3350 |
| | | *0.9982* | | *1.0192* |
| $\rho^K$ | × | × | -7.2690 | -8.6838 |
| | | | *2.3989* | *2.4577* |
| F-statistic (τ) | 104 | 107 | 101 | 103 |
| F-statistic (γ) | 90 | 90 | 87 | 87 |
| χ2(P) | × | 666 | × | 666 |
| χ2(K) | × | × | 519 | 519 |
| ξ(1-τ) | 0.1183 | 0.1394 | 0.0777 | 0.0967 |
| | *0.0430* | *0.0436* | *0.0433* | *0.0437* |
| observations | 420640 | 420640 | 420640 | 420640 |
| individuals | 151135 | 151135 | 151135 | 151135 |

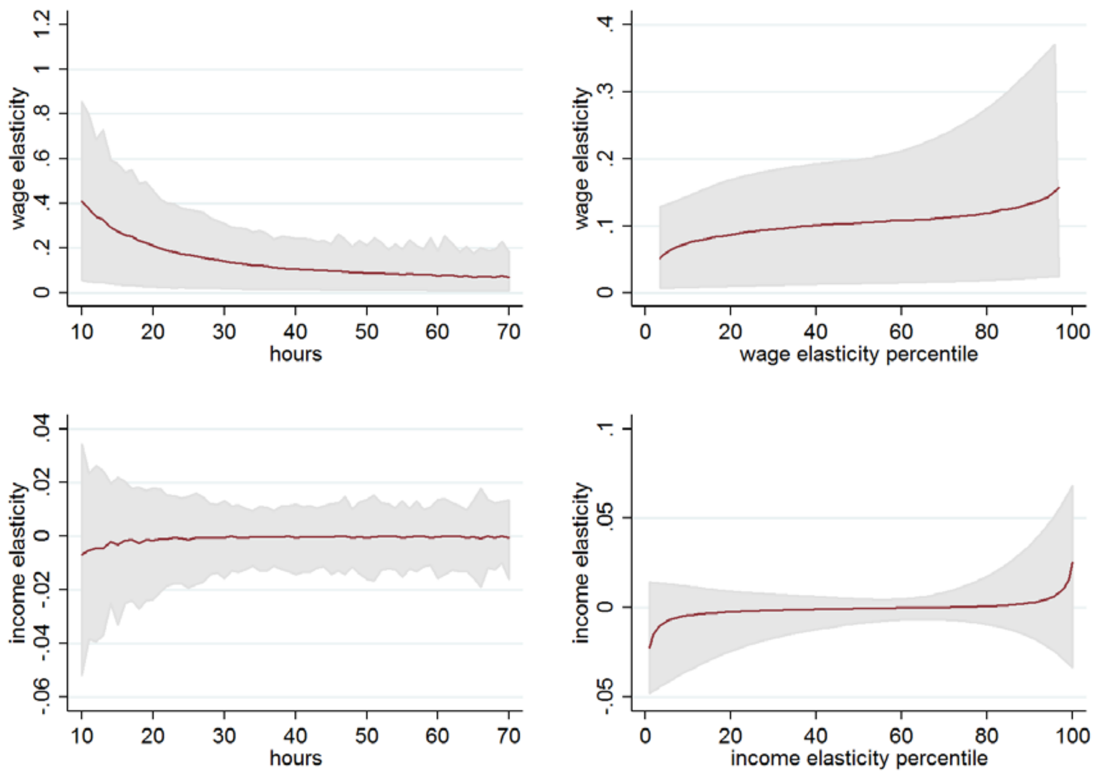
Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. The columns differ according to which inverse Mill's ratios are included to control for selection. Additional control variables included in the regressions but not shown are: individual dummies, age dummies, reference week dummies, year dummies, and as described in Table 3.1, marital status, presence of children, schooling, urbanicity. F-statistics are tests for significance of excluded instruments in the first stage OLS regressions. χ2 statistics are tests for significance of excluded instruments in the first stage probits. ξ(1-τ) are uncompensated wage elasticities evaluated at mean hours. All regressions are run using Labour Force Survey weights (coefqq, factor, faktorq) to make them population-representative.

F-statistics on excluded first stage instruments presented in Table 4.2 show they are relevant explanatory variables for marginal tax rates and other income. Similarly, chi-squared statistics for excluded instruments show they are relevant explanatory variables for participation and kink proximity. Throughout the remainder of the paper we use the specification presented in column (4) of Table 4.2 where we adjust for selection into participation and away from a kink point by means of inverse Mill's ratios.

## 4.3 Distributions of elasticities

While the elasticities presented in Table 4.2 are calculated at mean hours, we can also calculate elasticities for each observation in the data based on the same set of estimates. Distributions of these individual elasticities are presented in Figure 4.1.

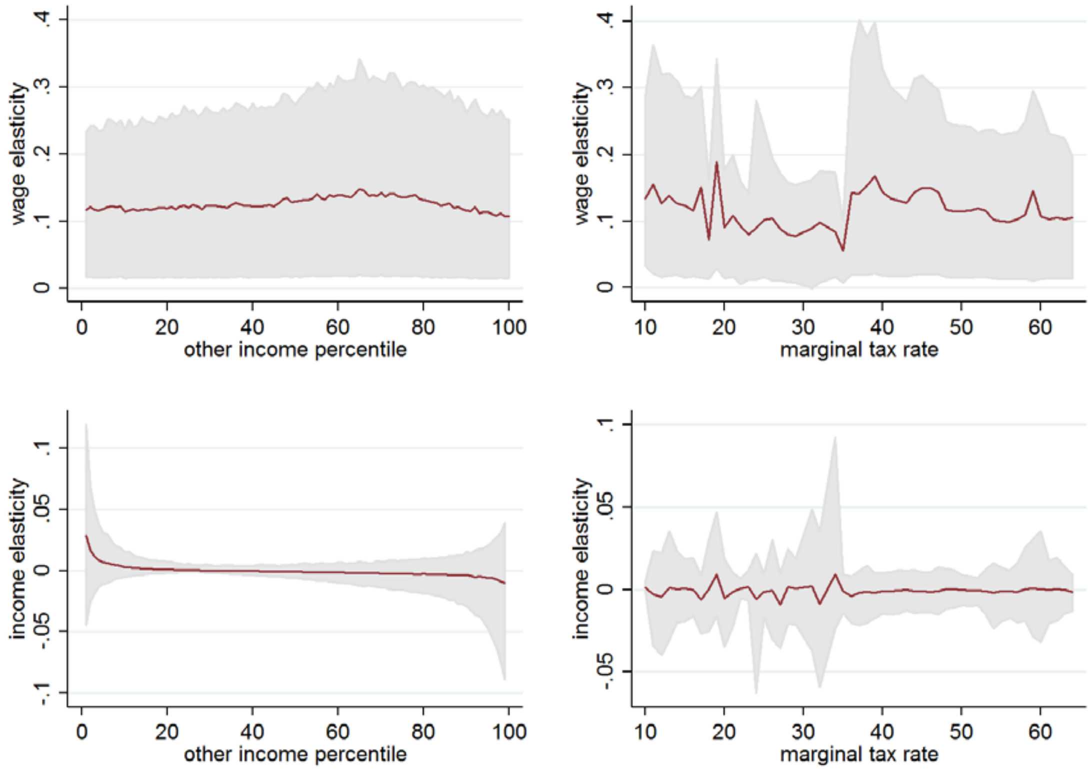
**Figure 4.1** Wage and income elasticity distributions by hours and elasticity percentile




Note: Distributions of elasticities are estimated from 1000 bootstrap replications. Individual elasticities are calculated and presented in the figures. The means of elasticities are shown with the red line and 95 percent confidence bands are shown with the grey shaded area. Wage elasticities are presented in the upper panes and income elasticities are presented in the lower panes. Panes on the left show elasticities across the hours distribution and panes on the right show elasticities by elasticity percentile. Specifications are as in column (4) of Table 4.2.

From the upper panes of Figure 4.1 we can see that wage elasticities are everywhere positive. The upper right pane reflects the assumed labour supply functional form, where elasticities are calculated by dividing the estimated coefficient by hours. Recall from the upper left pane of Figure 3.1 that there are only few observations with very low hours. Indeed, the upper right pane of Figure 4.1 shows wage elasticities range from 0.6 at percentile 2 to 1.5 at percentile 98. The lower panes of figure 4.1 present distributions of income elasticities, which are never significantly different from zero. Indeed, towards the middle of the income elasticity distribution, we observe more precisely estimated zero income elasticities.

**Figure 4.2** Wage and income elasticity distributions by other income and marginal tax rates



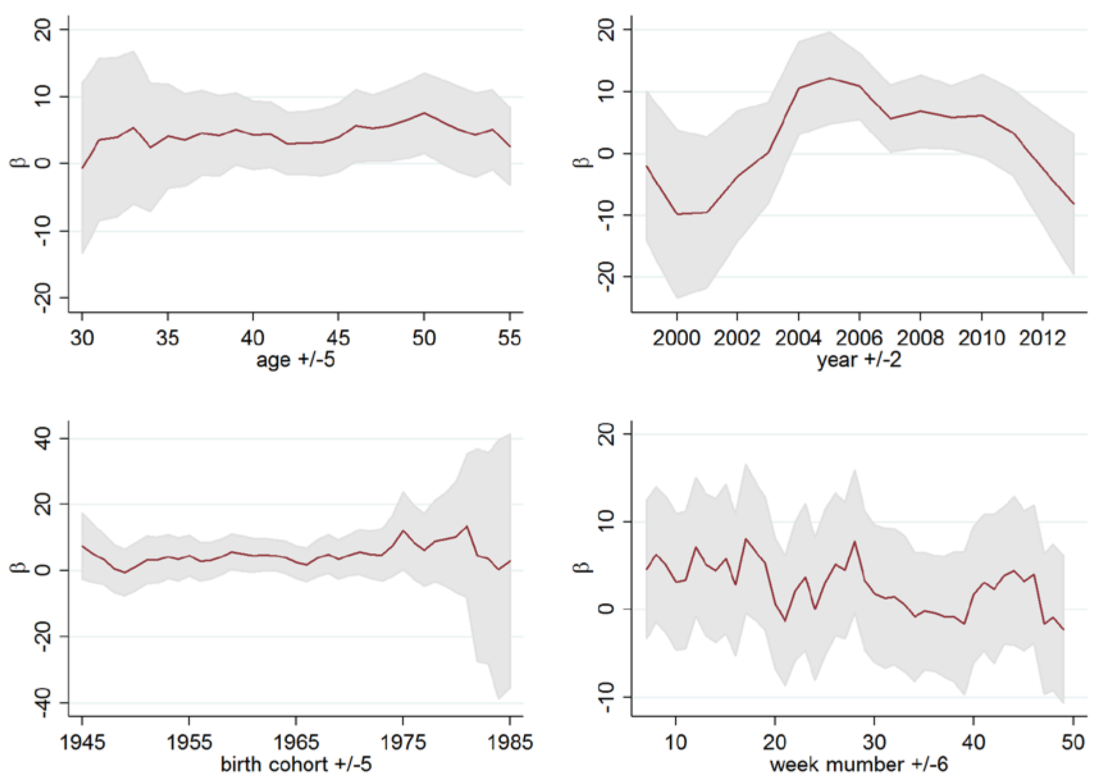

Note: Distributions of elasticities are estimated from 1000 bootstrap replications. Individual elasticities are calculated and presented in the figures. The means of elasticities are shown with the red line and 95 percent confidence bands are shown with the grey shaded area. Wage elasticities are presented in the upper panes and income elasticities are presented in the lower panes. Panes on the left show elasticities by percentile of other income and panes on the right show elasticities by marginal tax rate. Specifications are as in column (4) of Table 4.2.

In Figure 4.2 we present distributions of elasticities by endogenous variables. The left panes of Figure 4.2 show that wage and income elasticities are quite invariant across the distribution of other income. Elasticities are more variable across the distribution of marginal tax rates because, recall from the upper right pane of Figure 3.1, only few individuals have marginal tax rates below 40 percent.

## 4.4 Heterogeneity

Estimates presented so far have pooled all observations, estimating a single set of parameters for the whole population. In this sub-section we split the population into groups along different dimensions to look for heterogeneous responses by gender, martial status, presence and age of children, schooling, region, housing and occupational status. For each group we perform the whole analysis separately, estimating four new first stage regressions for each group as well as estimating separate hours functions.

**Figure 4.3** Beta estimated by age, year, cohort and week




Note: Beta estimated on various subsamples: by age in the upper left pane, by observation year in the upper right pane, by birth cohort in the lower left pane, by observation week in the lower right pane. Point estimates are shown with the red line and 95 percent confidence bands are shown with the grey shaded area. Specifications are as in column (4) of Table 4.2.

In Figure 4.3 we present heterogeneity in beta estimates by age, cohort, year and week. We split the data into (11-year) age groups and (11-year) birth cohorts in panes on the left, and into 5 calendar years, and 13 weeks of the year in panes on the left. In each of the panes we scroll through the data, estimating separately for each characteristic within each window. A general feature of these heterogeneity figures is that standard error bands become wider because of smaller sample sizes and only occasionally are group estimates significantly different from zero. The clearest tendency is for beta to be highest in the middle of the sample period, especially 2004-6, and somewhat 2007-10. Estimates are also highest at around age 50. Otherwise there is no significant heterogeneity by birth cohort or week of observation.

**Table 4.3** Estimates by gender and marital status

| | Male | Female | Single | Married | Single male | Single female | Married male | Married female |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| β | 0.6832 | 5.5568 | 7.0536 | 3.9315 | 2.7861 | 9.6116 | 0.6649 | 4.4446 |
| | *2.3379* | *2.2288* | *4.7321* | *1.7966* | *5.1194* | *10.1887* | *2.7180* | *2.2121* |
| γ | -0.3379 | -1.9609 | 1.0236 | 1.2823 | 0.9109 | -6.5596 | 1.6532 | -0.9230 |
| | *1.4072* | *1.4619* | *2.3526* | *1.4592* | *2.4334* | *3.2731* | *2.1242* | *1.6322* |
| $\rho^P$ | -2.2481 | -0.5056 | 2.2530 | 4.0616 | 1.6025 | -1.5411 | 3.1999 | -0.7131 |
| | *3.8098* | *1.1515* | *1.9530* | *1.1641* | *5.8529* | *2.0611* | *4.6743* | *1.3325* |
| $\rho^K$ | -4.3905 | -7.3040 | -14.6399 | 1.4799 | -17.6121 | -2.3050 | 4.8492 | -4.6327 |
| | *3.5085* | *2.7006* | *3.5053* | *3.2315* | *5.1322* | *3.6864* | *4.0583* | *3.5118* |
| F-statistic (τ) | 61 | 58 | 21 | 52 | 21 | 6 | 27 | 43 |
| F-statistic (γ) | 52 | 42 | 22 | 43 | 18 | 13 | 22 | 31 |
| χ2(P) | 140 | 425 | 300 | 397 | 95 | 156 | 65 | 310 |
| χ2(K) | 255 | 325 | 336 | 299 | 156 | 208 | 179 | 176 |
| ξ(1-τ) | 0.0169 | 0.1609 | 0.1895 | 0.1036 | 0.0711 | 0.2773 | 0.0162 | 0.1288 |
| | *0.0580* | *0.0645* | *0.1272* | *0.0474* | *0.1306* | *0.2940* | *0.0662* | *0.0641* |
| Observations | 207952 | 212688 | 143671 | 272770 | 74842 | 68829 | 131001 | 141769 |
| Individuals | 74732 | 76403 | 53579 | 97256 | 27905 | 25674 | 46698 | 50558 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different splits of the sample: Columns (1) and (2) by gender; (3) and (4) by marital status; (5) to (8) by the interaction of gender and marital status. Specifications are as in column (4) of Table 4.2.

In Table 4.3 we present estimates by gender and marital status. The wage elasticity for women is large and significant, but the elasticity for men is insignificant. While singles have higher point elasticities than married individuals, the differences are insignificant. Considering the interaction of gender and marital status, only wage elasticities for married women are significant. While the point estimate of the wage elasticity is highest for single women, this estimate is insignificant, and the F-statistics on excluded instruments for marginal tax rates suggest instruments are weak for this subsample.

**Table 4.4** Estimates by age of youngest child

| | youngest child 0-2 | youngest 3-6 | youngest 7-9 | youngest 11-14 | youngest 15-17 | no children |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | 2.7046 | 4.2379 | 10.9698 | 3.0435 | -5.4194 | 4.7714 |
| | *5.2659* | *4.2389* | *5.4013* | *4.0536* | *4.8335* | *2.9397* |
| $\gamma$ | -0.4537 | -2.3720 | 1.5703 | 0.4156 | 0.4665 | -0.4942 |
| | *3.8664* | *3.3077* | *3.3537* | *2.8110* | *5.9184* | *1.4839* |
| $\rho^P$ | 1.7712 | 5.8382 | 19.1985 | -0.5502 | 0.3738 | -0.7698 |
| | *1.7164* | *3.8895* | *5.1766* | *5.5011* | *5.8161* | *3.4036* |
| $\rho^K$ | -11.4084 | -11.3570 | 26.0893 | -6.9692 | 11.4385 | -6.9361 |
| | *7.5346* | *8.3812* | *9.2295* | *7.4001* | *7.8436* | *3.2215* |
| F-statistic ($\tau$) | 10 | 15 | 7 | 13 | 6 | 59 |
| F-statistic ($\gamma$) | 8 | 9 | 6 | 13 | 4 | 54 |
| $\chi 2(P)$ | 436 | 25 | 20 | 24 | 14 | 158 |
| $\chi 2(K)$ | 65 | 45 | 33 | 40 | 46 | 348 |
| $\xi(1-\tau)$ | 0.0708 | 0.1125 | 0.2894 | 0.0800 | -0.1414 | 0.1277 |
| | *0.1378* | *0.1125* | *0.1425* | *0.1065* | *0.1261* | *0.0787* |
| observations | 36850 | 43785 | 27864 | 47982 | 27642 | 214947 |
| individuals | 14807 | 16958 | 10814 | 17998 | 10554 | 78981 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different samples according to age of youngest child in columns (1) to (5) and for individuals without children under the age of 18 in the household in column (6). Children presence and age is at 1 January in the reference year. Specifications are as in column (4) of Table 4.2.

Estimates by age of youngest child in the household are presented in Table 4.4. F-statistics on excluded instruments show that instruments are weak in all cases except for households without children. However, even for these households, the wage elasticity is insignificantly different from zero.

**Table 4.5** Estimates by highest completed schooling

| | Compulsory | High school | College |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\beta$ | 0.7618 | 0.7629 | 9.2190 |
| | *5.1882* | *2.7281* | *2.6279* |
| $\gamma$ | -4.4907 | -4.0471 | -2.2747 |
| | *4.2069* | *2.7455* | *1.8640* |
| $\rho^P$ | 3.5733 | 5.2854 | 6.8376 |
| | *3.2763* | *1.5345* | *1.3659* |
| $\rho^K$ | -7.3992 | 1.7815 | -20.1314 |
| | *4.9618* | *3.4200* | *4.3184* |
| F-statistic ($\tau$) | 12 | 21 | 41 |
| F-statistic ($\gamma$) | 9 | 16 | 33 |
| $\chi 2(P)$ | 107 | 339 | 272 |
| $\chi 2(K)$ | 126 | 308 | 125 |
| $\xi(1-\tau)$ | 0.0204 | 0.0202 | 0.2435 |
| | *0.1387* | *0.0724* | *0.0694* |
| Observations | 72769 | 191013 | 155668 |
| Individuals | 26770 | 68805 | 55437 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different samples according to highest completed schooling. The education ministry defines the minimum enrolled time normally required to complete each qualification. Statistics Denmark defines highest completed schooling as the qualification corresponding to the highest minimum enrolled time. Specifications are as in column (4) of Table 4.2.

Estimates by highest completed level of schooling are presented in Table 4.5. Instruments are weak for those with only compulsory schooling. However, for college graduates the instruments are relevant as shown by F-statistics, and the wage elasticity is significant and large, and more than twice the size of the elasticity for the population as a whole.

**Table 4.6** Estimates by municipal taxes and municipal earnings

| | Hi-earning municipality | Lo-earning municipality | High tax municipality | Low tax municipality |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\beta$ | 5.9989 | -0.9660 | 3.6202 | 1.2608 |
| | *2.4350* | *2.6454* | *2.0925* | *3.0347* |
| $\gamma$ | 1.0807 | -8.7067 | -1.5574 | -3.8638 |
| | *1.1392* | *2.9102* | *1.2108* | *2.5434* |
| $\rho^P$ | 3.4402 | 4.5745 | 4.9346 | 5.2638 |
| | *1.4513* | *1.4620* | *1.2139* | *1.9545* |
| $\rho^K$ | -8.3921 | -8.2661 | -13.8799 | -5.0499 |
| | *3.6544* | *3.4753* | *2.7827* | *4.4547* |
| F-statistic ($\tau$) | 63 | 21 | 77 | 19 |
| F-statistic ($\gamma$) | 65 | 17 | 70 | 16 |
| $\chi 2(P)$ | 281 | 395 | 523 | 155 |
| $\chi 2(K)$ | 224 | 311 | 411 | 183 |
| $\xi(1-\tau)$ | 0.1595 | -0.0256 | 0.0967 | 0.0330 |
| | *0.0648* | *0.0702* | *0.0559* | *0.0795* |
| Observations | 195895 | 221583 | 318141 | 95794 |
| Individuals | 70096 | 80708 | 112934 | 37473 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different groups of municipalities of residence. Municipalities are ranked according to mean earnings and for columns (1) and (2) the sample is split by municipality mean above or below median of municipality means. Municipalities are ranked according to mean marginal tax rates and for columns (3) and (4) the sample is split by municipality mean above or below median of municipality means. Specifications are as in column (4) of Table 4.2.

We can group regions of residence in various ways. In Table 4.6 we split municipalities according to whether average municipal earnings are above or below median (of averages) for all municipalities, and whether the marginal tax rate to be paid on 300,000 earnings on average for the municipality is above or below median (of averages) for all municipalities. Among all of these splits, only those who are resident in high earnings municipalities have significant wage elasticities.

**Table 4.7** Estimates by region and urbanicity

| | Jutland | Zealand | High urbanicity | Medium | Low |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\beta$ | 0.9277 | 5.2254 | 4.2023 | 4.4625 | -1.2681 |
| | *2.6255* | *2.4958* | *2.6299* | *3.5425* | *3.6486* |
| $\gamma$ | -6.1513 | 1.4832 | -1.0071 | -0.2690 | -9.7119 |
| | *2.5854* | *1.1676* | *1.1441* | *2.6666* | *4.5387* |
| $\rho^P$ | 3.7173 | 2.9751 | 4.8046 | 3.5412 | 3.8804 |
| | *1.4426* | *1.6126* | *1.7422* | *1.7829* | *1.7885* |
| $\rho^K$ | -6.2588 | -8.1801 | -13.3114 | -7.6702 | -4.6666 |
| | *3.5940* | *3.7474* | *4.0117* | *4.3678* | *4.2604* |
| F-statistic ($\tau$) | 26 | 60 | 60 | 17 | 8 |
| F-statistic ($\gamma$) | 21 | 62 | 68 | 16 | 8 |
| $\chi 2(P)$ | 382 | 215 | 233 | 202 | 260 |
| $\chi 2(K)$ | 246 | 200 | 192 | 157 | 198 |
| $\xi(1-\tau)$ | 0.0245 | 0.1389 | 0.1131 | 0.1183 | -0.0333 |
| | *0.0695* | *0.0664* | *-0.0271* | *-0.0071* | *-0.2552* |
| Observations | 196675 | 168647 | 134261 | 113876 | 167110 |
| Individuals | 70551 | 60885 | 49405 | 41827 | 60150 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different groups of municipalities of residence. Columns (1) and (2) contrast Jutland and Zealand; columns (3)-(5) split municipalities according to urbanicity. Specifications are as in column (4) of Table 4.2.

Grouping municipalities by broad region and urbanicity as in Table 4.7 shows that Zealand is the only significant grouping. Urban and semi-urban municipalities have higher point estimate elasticities than rural areas, but the difference is insignificant.

**Table 4.8** Estimates by home ownership and industrial sector

| | Home owner | Home renter | Public sector | Private sector |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| β | 5.9408 | -5.8451 | 8.8667 | 3.6166 |
| | *2.1174* | *5.0823* | *3.5548* | *1.9547* |
| γ | 2.4762 | -16.6991 | -3.0204 | 0.6692 |
| | *1.3739* | *6.5870* | *2.0028* | *1.2357* |
| $\rho^P$ | 2.9784 | 3.5703 | 5.4298 | 3.5725 |
| | *1.1166* | *2.2388* | *1.8689* | *1.4025* |
| $\rho^K$ | -1.8480 | -17.8122 | -14.2218 | -6.8406 |
| | *3.4678* | *3.9716* | *4.8432* | *3.0208* |
| F-statistic (τ) | 51 | 11 | 46 | 72 |
| F-statistic (γ) | 48 | 11 | 30 | 58 |
| χ2(P) | 397 | 345 | 193 | 552 |
| χ2(K) | 261 | 284 | 91 | 379 |
| ξ(1-τ) | 0.1532 | -0.1640 | 0.2489 | 0.0935 |
| | *0.0546* | *0.1426* | *0.0998* | *0.0506* |
| Observations | 272684 | 142709 | 127036 | 232470 |
| Individuals | 97135 | 53561 | 46238 | 84597 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different home ownership groups in columns (1) and (2), and for different employment sectors in columns (3) and (4). Home ownership if defined as having a positive owned home value (*ejendomsvurdering*). Public sector employment is defined from variable *db03* and is first observed from year 2000. Specifications are as in column (4) of Table 4.2.

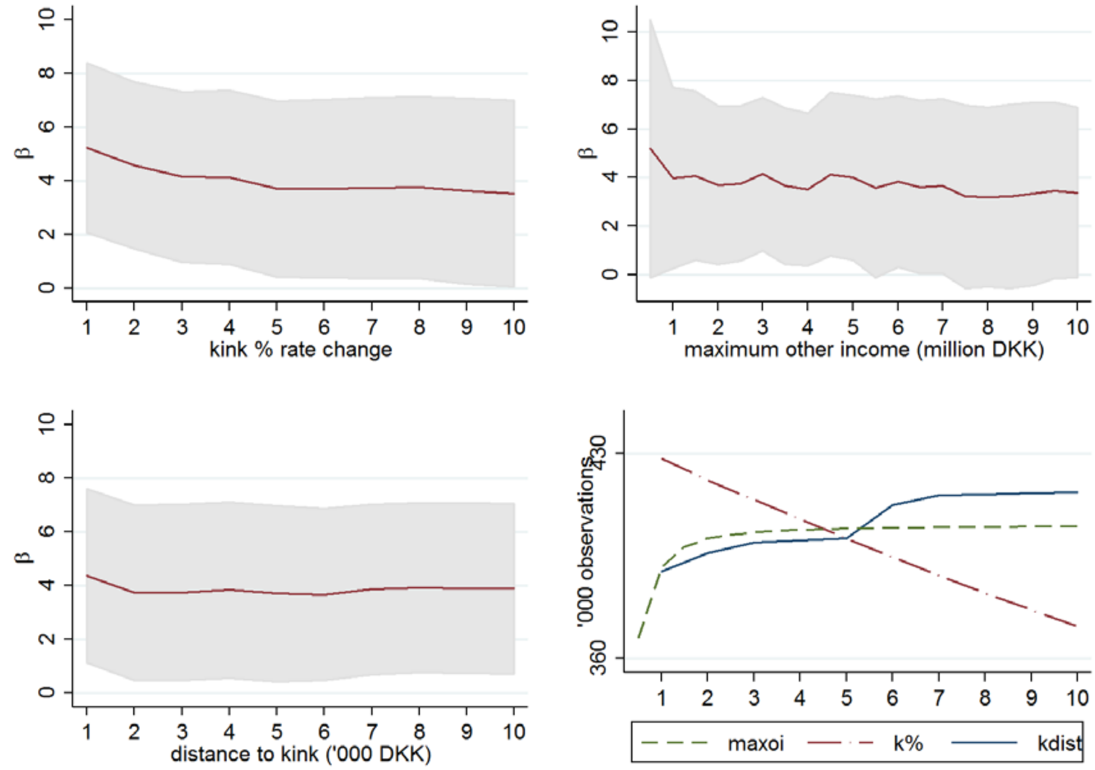
In a final set of groups, Table 4.8 presents estimates by accommodation ownership status and sector of occupation. Those who own their home and those working in the public sector have higher wage elasticities than those renting and working in the private sector respectively.

The heterogeneity analyses have yielded several insights into which sub-samples are driving the behavioural responses found for the population as a whole. Of all groups, the college educated are the most responsive, with the highest wage elasticities. Other relatively responsive groups are females, especially married women; regionally, those living in Zealand and in high earning municipalities are most responsive; by sector, home-owners and public sector workers have highest elasticities.

## 4.5 Robustness checks

For our estimations so far, we have made a number of assumptions regarding data construction and sampling. In this section we examine how robust our estimates are to some of these assumptions by running a series of sensitivity checks. We consider the inclusion of outliers, definition of budget constraint kinks and proximity, mobility between municipalities, definition of hours and reasons for unusual hours, certain weeks in the year, and ongoing education.

**Figure 4.4** Beta sensitivity to other income outliers and kink definition




Note: Beta estimated with various sample restrictions. In the upper right pane estimates are presented with different exclusions for outliers in other income, fixing the kink definition as a 5 percent change within 5,000 kr. of observed earnings. The upper left pane shows estimates defining a kink in the budget constraint as different percentage changes in the marginal tax rate, fixing kink proximity as within 5,000 kr. of observed earnings and defining other income outliers as greater than 2 million kr. The lower left pane shows estimates defining a kink in the budget constraint as within different ranges of earnings, fixing the kink definition as a 5 percent change in the marginal tax rate and defining other income outliers as greater than 2 million kr. The lower right panel shows number of observations used in the regressions presented in the other panes. Point estimates are shown with the red line and 95 percent confidence bands are shown with the grey shaded area. Specifications are as in column (4) of Table 4.2.

Sensitivity of estimates to sample inclusion is presented in Figure 4.4. In the top right pane we consider the definition of outliers in other income as one exclusion criteria from the whole analysis. Estimates become insignificant when we exclude everyone with other income above 500,000, because this is a large proportion of the sample as can be seen from the bottom right pane. Estimates also become insignificant when only removing outliers with other income above 5.5 million, probably because these extreme values are exerting their influence. Our preferred specification defines outliers as having more than 2 million in unearned income.

The left panes of Figure 4.4 show sensitivity to kink definition. That there are a range of marginal tax rate changes along the budget constraint is illustrated by observation counts in the lower right pane. In terms of the size of marginal tax rate change defining a kink in the upper left pane, estimates fall somewhat moving from 1 to 5 percent but are flat thereafter up to 10 percent. Our preferred specification defines a kink as a 5 percent marginal tax rate change. In terms of proximity to kink defining exclusion from the hours regression, the lower left pane shows estimates are stable for a range of distances. Our preferred kink proximity definition is 5,000.

**Table 4.9** Estimates by hours measure and non-movers

| | actual hours total | actual main job | same municipality |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\beta$ | 3.6421 | 3.7370 | 4.2458 |
| | *1.6466* | *1.5549* | *1.7937* |
| $\gamma$ | -0.9293 | -0.4691 | -0.4886 |
| | *1.0869* | *1.0379* | *1.1575* |
| $\rho^P$ | 3.3350 | 1.8197 | 3.9030 |
| | *1.0192* | *0.9725* | *1.0731* |
| $\rho^K$ | -8.6838 | -5.9038 | -9.3415 |
| | *2.4577* | *2.3301* | *2.5624* |
| F-statistic ($\tau$) | 103 | 104 | 87 |
| F-statistic ($\gamma$) | 87 | 87 | 78 |
| $\chi 2(P)$ | 666 | 622 | 609 |
| $\chi 2(K)$ | 519 | 522 | 507 |
| $\xi(1-\tau)$ | 0.0967 | 0.1007 | 0.1128 |
| | *0.0437* | *0.0419* | *0.0477* |
| observations | 420640 | 418217 | 391357 |
| individuals | 151135 | 150460 | 141828 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different measures of hours worked in columns (1) and (2), where column (1) reproduces our main estimates for total actual hours worked from Table 4.2 column 4, and column (2) only considers actual hours worked in the main job, ignoring hours in a second job. Column (3) includes only individuals who do not change municipality of residence during their Labour Force Survey observation years. Specifications are as in column (4) of Table 4.2.

Our hours of work measure is the sum of responses to labour force survey questions about actual hours worked in the reference week in the main job and in a secondary job. These preferred estimates are presented again in Table 4.9 column (1), alongside estimates based on actual hours worked in the main job only presented in column (2). Elasticities are unchanged.

One concern about the analysis so far is that we are treating changes in tax rate instruments as exogenous year to year. Those changing municipality of residence between observations will probably have different values of tax rate instruments as a consequence of the move; if the characteristics of movers are correlated with the tax rate changes, estimates might be biased. In column (3) of Table 4.9, we restrict our sample to individuals not changing municipality between observations. Point estimates of non-movers are slightly higher than for the population as a whole, but not significantly different. These similar results suggest mobility between municipalities is not giving rise to bias.

**Table 4.10** Estimates excluding unusual hours

| | 2000-2015 | Hours vary | Holiday | Sickness | Slack | Any reason |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | 4.6304 | 4.3857 | 3.4852 | 4.6709 | 4.6271 | 2.2546 |
| | *1.7025* | *1.8849* | *1.6968* | *1.6837* | *1.7290* | *1.8786* |
| $\gamma$ | -0.4424 | -0.5438 | -0.7403 | -0.3008 | -0.4714 | -1.3546 |
| | *1.0708* | *1.1865* | *1.0827* | *1.0464* | *1.0604* | *1.1199* |
| $\rho^P$ | 2.9913 | 1.6803 | 1.7555 | 3.0430 | 2.7663 | 0.5725 |
| | *1.0716* | *1.1197* | *1.0776* | *1.0659* | *1.0674* | *1.0842* |
| $\rho^K$ | -10.2866 | -9.5337 | -12.1544 | -10.5433 | -9.9790 | -10.6407 |
| | *2.5094* | *2.8039* | *2.4915* | *2.5077* | *2.5345* | *2.7600* |
| F-statistic ($\tau$) | 108 | 83 | 97 | 108 | 109 | 74 |
| F-statistic ($\gamma$) | 89 | 68 | 80 | 90 | 92 | 61 |
| $\chi 2(P)$ | 711 | 651 | 653 | 710 | 738 | 605 |
| $\chi 2(K)$ | 482 | 437 | 460 | 474 | 470 | 389 |
| $\xi(1-\tau)$ | 0.1231 | 0.1180 | 0.0901 | 0.1235 | 0.1228 | 0.0582 |
| | *0.0453* | *0.0507* | *0.0439* | *0.0445* | *0.0459* | *0.0485* |
| observations | 366601 | 288963 | 327213 | 360710 | 360243 | 238587 |
| individuals | 131143 | 109346 | 120580 | 129604 | 129515 | 93430 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different samples excluding observations where actual hours differ from normal hours. The variable containing the reason for hours deviation (hourreas) is available first in year 2000. In column (1) for reference we present estimates for everyone observed 2000-15 regardless of whether actual and normal hours are different. Columns (2) to (5) exclude observations where actual hours are different from normal hours for each of four specific reasons, and column (6) excludes observations where hours deviate for any reason. Specifications are as in column (4) of Table 4.2.

Our outcome of interest is actual hours worked in the reference week. However, for many individuals, actual hours depart from normal hours worked. In Table 4.10 we examine whether estimates are sensitive to these departures. In columns (2) to (5) we consider specific reasons for unusual actual hours. Holidays as the reason for irregular hours are the only reason for elasticities to be somewhat smaller, though not significantly smaller than estimates for the population as a whole. When removing all observations with unusual hours, estimates in column (6) become insignificant because this is a large proportion of the sample.2[nd]

**Table 4.11** Robustness checks by week

| | Shortest week | 2nd shortest | 3rd shortest | 4th shortest | Week*year |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| β | 3.6391 | 3.5523 | 3.6832 | 3.6981 | 3.6369 |
| | *1.6464* | *1.6699* | *1.6878* | *1.6881* | *1.6243* |
| γ | -0.9159 | -0.9593 | -0.8363 | -0.8308 | -0.7679 |
| | *1.0902* | *1.0959* | *1.1017* | *1.0945* | *1.0621* |
| $\rho^P$ | 3.2371 | 1.7723 | 1.5388 | 1.1515 | 3.7676 |
| | *1.0214* | *1.0281* | *1.0452* | *1.1130* | *1.0201* |
| $\rho^K$ | -8.6960 | -7.9727 | -7.8298 | -8.3948 | -9.1269 |
| | *2.4544* | *2.4784* | *2.4850* | *2.5211* | *2.4236* |
| F-statistic (τ) | 102 | 99 | 98 | 101 | |
| F-statistic (γ) | 87 | 84 | 83 | 86 | |
| χ2(P) | 667 | 688 | 733 | 788 | |
| χ2(K) | 519 | 507 | 515 | 505 | |
| ξ(1-τ) | 0.0966 | 0.0939 | 0.0974 | 0.0978 | 0.0966 |
| | *0.0437* | *0.0442* | *0.0446* | *0.0446* | *0.0431* |
| observations | 420010 | 413253 | 406964 | 400342 | 420640 |
| individuals | 150964 | 148910 | 146858 | 144762 | 151135 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. In column (1) the regression is run on a sample excluding the week of the year with the shortest hours; in column (2) the two shortest weeks are excluded; three shortest weeks are excluded for column (3) and four shortest weeks are excluded for column (4). Specifications are as in column (4) of Table 4.2. For column (5), all observations are included, but instead of including (17) dummies for year of observation and (52) dummies for week or observation separately, we include (950) dummies for the interaction of week and year. Mills ratios for column (5) are calculated from probit estimates presented in Table 4.1, i.e. without interactions of years and weeks. However, first stage OLS estimates of log(1- τ) and γ do include interactions of year and week.

Some weeks of the year have fewer potential work hours because of public holidays or industry holidays. In our main specification we control for week and year separately, but because some public holidays are on different weeks in different years, the relevant pattern may not be captured. In Table 4.11 we consider sensitivity to weeks of year. For columns (1) to (4) we drop the weeks of each year with the fewest average hours worked, and estimates are completely unchanged. In column (5) we include a large set of controls by interacting week and year, finding that estimates are also unchanged.

**Table 4.12** Estimates excluding the young and those under education

| | Not studying | Over 25 | Over 27 | Over 29 | Over 31 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\beta$ | 3.5780 | 4.4173 | 3.6590 | 3.5503 | 3.6427 |
| | *1.6701* | *1.6616* | *1.6732* | *1.6892* | *1.7095* |
| $\gamma$ | -0.0573 | 0.0408 | 0.1375 | 0.6174 | 0.7128 |
| | *1.1439* | *1.1408* | *1.2186* | *1.2849* | *1.3199* |
| $\rho^P$ | 3.4279 | 3.5878 | 3.0442 | 2.6253 | 2.7684 |
| | *1.0059* | *1.0290* | *1.0652* | *1.1730* | *1.3352* |
| $\rho^K$ | -5.5945 | -7.7660 | -7.1514 | -5.5699 | -4.9185 |
| | *2.5737* | *2.5010* | *2.5827* | *2.7278* | *2.8338* |
| F-statistic ($\tau$) | 86 | 92 | 75 | 66 | 61 |
| F-statistic ($\gamma$) | 74 | 77 | 63 | 56 | 53 |
| $\chi2(P)$ | 564 | 634 | 574 | 469 | 380 |
| $\chi2(K)$ | 482 | 502 | 478 | 419 | 384 |
| $\xi(1-\tau)$ | 0.0942 | 0.1170 | 0.0967 | 0.0937 | 0.0961 |
| | *0.0440* | *0.0440* | *0.0442* | *0.0446* | *0.0451* |
| Observations | 411724 | 413514 | 397850 | 380976 | 362374 |
| Individuals | 147840 | 148457 | 142593 | 136219 | 129300 |

Note: Model estimates and *standard errors in italics*. Each column contains coefficients of interest from separate second stage IV regressions with dependent variable actual hours worked. Regressions are run for different sample restrictions by educational enrolment and age. Column (1) excludes individuals enrolled in an education on 1 January in the reference year (igudd). Columns (2) to (5) increase the minimum age for sample inclusion. Specifications are as in column (4) of Table 4.2.

Our main sample includes individuals aged 25-59. However, the young may still be studying or just entering the labor market and respond to tax incentives in different ways. In Table 4.12 we analyze sensitivity to related sample inclusion criteria. In column (1) we drop individuals observed at any time to be enrolled in a course of study (leading to a formal qualification recognized by the education ministry). In columns (2) to (5) we increase the minimum age for inclusion in the sample. Estimates are invariant to any of these exclusion criteria.

In this sub-section we have seen that estimates are robust to all of our sample inclusion criteria: outliers and kink definitions, age when joining the sample and educational enrolment, and mobility between municipalities. Estimates are also robust to hours definition, specific reasons for unusual hours, holidays and specific survey weeks.

# 5 Conclusion

We have estimated labour supply responses to tax reforms in Denmark using data from Labour Force Surveys spanning 1997-2015, finding uncompensated wage elasticities (at mean hours) of 0.096, and insignificant income elasticities. Estimates are robust to a number of sensitivity checks, and we find a good deal of heterogeneity in responses between sub-samples; those with a college degree have a wage elasticity of 0.244 and women have a wage elasticity of 0.161.

Our estimated elasticities are within the range of previous Danish findings, but several differences between studies make reconciliation difficult. The three other studies used different methods and indeed made specific methodological contributions. Bingley and Lanot (2002) estimate hours and gross wage responses to income tax changes for private sector workers, finding an uncompensated wage elasticity of 0.141. Frederiksen and co-authors (2008) estimate labour supply responses explicitly focusing on overtime work and secondary jobs, finding elasticities of 0.053 for men and 0.148 for women. Chetty and co-authors (2011) estimate a model of labour supply with adjustment costs and firm hours constraints, finding wage elasticities of 0.02. In contrast to these three studies, we claim no methodological contribution, instead applying the approach of Blundell and co-authors (1998) to Danish data for the first time.

Our contribution with respect to other Danish studies is estimation of a labour supply model that is consistent with intertemporal optimization. Furthermore, we use more recent 1997-2015 data compared to Bingley and Lanot using 1980-91, Frederiksen using 1996, and Chetty using 1994-2001. The labour supply measure we use from the Labour Force Survey is a standard Eurostat-wide question about actual hours worked, as opposed to the one-time survey of hours used by Frederiksen and the administrative data on annual earnings used by Bingley and Lanot and Chetty. We show elasticities to be quite heterogeneous between sub-samples; such heterogeneity is not elaborated in other Danish studies.

There are at least three caveats to be borne in mind. First, we assume a specific functional form for labour supply responses; a functional form that has attractive properties and has been used elsewhere, but we do not present results from alternative labour supply functions. Second, while our definition of other income is constructed so as to be life-cycle consistent, we are essentially imputing consumption from income minus saving derived from administrative data on wealth changes, which might be a noisy measure compared to survey questions about expenditure based on diary records, as have been used elsewhere. Third, certain tax reforms might affect decisions at the extensive as well as the intensive margin; we model labour supply conditional on working, and have ignored the work participation decision, beyond controlling for sample selection.

Future work could usefully incorporate labour force participation decisions. However, while our approach of linearizing the budget constraint deals well with progressive taxes, it is less suited for budget constraint discontinuities, and a discrete response model would be more appropriate. The rolling panel structure of Labour Force Surveys allows us to deal with unobserved individual heterogeneity, but because individuals are typically observed in only two or three tax years, this data offers little scope for modelling the dynamics of labour supply and saving. In recent years, Danish administrative data on hours worked has become more reliable, and with broader coverage of the population. This new data should facilitate estimation of theory-consistent models incorporating richer behavioural dynamics.

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