Aggregation and Intertemporal Labor Supply

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Abstract

This paper develops an aggregation procedure for dynamic labor supply choices of workers who differ in their preferences, income, wealth, and labor market status. The method is theorybased, but requires neither a preference structure nor distributional assumptions for explanatory variables. It serves to qualitatively illustrate the main components of aggregate labor supply and the associated Frisch-wage elasticity. We quantify each component using micro-level panel data from the German SOEP. Self-reported reservation wages of unemployed workers and actual wages of employed workers are key to measuring the adjustment along the extensive and the intensive margin, respectively. Our empirical results demonstrate that (i) aggregation is quantitatively important and (ii) the relative importance of the two margins depends on the type of panel considered.

Keywords: Aggregation, Reservation Wages, Intensive and Extensive Margin, Frisch Wage-Elasticities JEL-Codes: C51, E10, J22

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1 Introduction

Aggregating individual economic choices that heterogeneous agents make in an uncertain environment is essential for any analysis that is concerned with the effect that a particular policy measure has on outcomes of large groups. Albeit essential and complex, it has been known since the work of Sonnenschein, Mantel and Debreu in the 1970s that aggregating wellbehaved individual supply or demand functions in such a way that the outcome reflects the assumed characteristics from the underlying individual functions is impossible. In light of this negative theoretical result applied research has addressed the need to aggregate by taking more practical routes. Modern macroeconomics with its emphasis on dynamic stochastic models and micro-founded decisions has addressed the challenge by operating for decades with the fiction of a representative agent. Thus, it effectively ignored individual heterogeneity. It also ignored the fact that estimates of key model parameters from micro level data typically differ by an order of magnitude from what is needed to replicate corresponding aggregate measures. A striking example is the Frisch wage-elasticity of labor supply - a key entity for policy analysis in a business cycle context. It is roughly 2.0 when derived from aggregate data that covers an entire economy, but it varies between zero and .6 when derived from micro-level data for men only.¹ Empirical research has taken an equally pragmatic approach by simplifying the complex aggregation problem along various dimensions. Blundell and Stoker (2005) survey the literature on empirical aggregation procedures that have been developed for the analysis of consumers' goods demand or labor market participation decicions.

In this paper, we develop an aggregation procedure for dynamic labor supply choices of heterogeneous individuals and use it to qualitatively illustrate the main components of an implied aggregate variable. We empirically implement it using individual panel data together with parametric and non-parametric estimation techniques. We illustrate the quantitative importance of the various components of the aggregate. In our setting heterogeneity relates to preferences, income, wealth, and labor market status. Our aggregation approach has the distinct advantage that it is theory-

¹See, e.g., MaCurdy (1981; 1985) and Altonji (1986).

based, yet requires neither a particular preference structure nor specific distributional assumptions for explanatory variables. It departs from optimal labor supply choices that individuals make in an uncertain environment and aggregates them to group-specific counterparts, thereby explicitly creating a bridge from individual choices to implied aggregate variable(s). The procedure is general and flexible enough to be in principle applicable to a vast set of alternative labor supply theories and extendable to a full-fledged macroeconomic analysis. Given our focus on aggregation in a dynamic context, we take as workhorse model MaCurdy's (1985) intertemporal labor supply model which has been studied extensively. It features complete markets, uncertainty and worker heterogeneity in observable and unobservable characteristics and allows us to easily retrieve the Frisch wage-elasticity of labor supply as our organizing principle. First we derive the intertemporal labor supply function for an individual worker. To formally illustrate the role that various model components play for an aggregate measure of labor supply and the way it reacts to a small, anticipated temporary wage rise across all workers in the model population, we modify the procedure developed by Paluch, Kneip, and Hildenbrand (2012) and allow for a corner solution in the worker's labor supply decision.² The extensive margin thus corresponds to employment with positive hours worked vs. unemployment. We show that the implied aggregate Frisch wage-elasticity of labor supply depends on (i) the intensive and extensive adjustment of hours worked, (ii) the extensive adjustment of wages, and (iii) the aggregate employment rate. Moreover, all adjustments along the extensive margin depend on the joint distribution of reservation wages and actual wages.

To illustrate the practicul usefulness of our aggregation procedure, we use the German Socio-Economic Panel (SOEP), a micro-level panel that is particularly well suited for the exercise. The SOEP is one of the few micro panels that provides evidence on unemployed workers' reservation wage rates. This variable is essential for estimating the adjustment of hours worked and wages paid of workers who change between unemployment and employment in reaction to a small wage rise – so-called movers. For estimating the adjustment of hours worked along the intensive margin,

²Paluch et al. (2012) designed their aggregation method to study links between consumption expenditure and non-labor income at the individual and aggregate level.

i.e., of stayers, we take advantage of the panel structure and estimate a standard panel model. That way we eliminate all unobserved individual fixed effects that arise from our dynamic setting.³ Our sample covers the period from 2000 to 2013. It comprises as our large group of interest males at working age who live in former West Germany. They account for ca. two-thirds of the entire work volume in 2000. The estimation results from our unbalanced panel yield an individual Frisch wage-elasticity of .50 - a value that is significantly smaller than the estimated aggregate values which vary between .85 and 1.06 over the sample. The intensive and the extensive margin of adjustment contribute equally to the overall variation in aggregate hours worked. If estimated on a balanced panel, the individual elasticity drops to .20, and the extensive margin becomes significantly more important for the overall variation in aggregate hours.

Our work relates to two main strands of the literature. There is the micro literature on intertemporal labor supply that has produced estimates of the individual wealth-compensated wage elasticity of hours worked since the pioneering work by MaCurdy (1981; 1985) and Altonji (1986). Their estimates from a balanced sample of permanently married men in the US range from .10 to .45, and from 0 to .35, respectively. Pistaferri (2003) disentangles the effect that anticipated and unanticipated wage changes have on individual labor supply. Using unique data on individual earnings expectations allow him to avoid IV estimation. He reports a Frisch wageelasticity equal to .7. Our results for the intensive margin are in line with these findings.⁴ Our work also relates to modern business cycle analysis that has grown out of the seminal paper by Lucas and Rapping (1969) and that focuses on the role of labor in a dynamic context. Most of these papers emphasize the importance of the aggregate Frisch wage-elasticity of labor supply for their respective mechanism. Chang and Kim (2005; 2006) allow for worker heterogeneity and explore how the size of the aggregate Frisch elasticity of hours worked varies with incomplete markets. They focus on the intensive margin only. Gourio and Noual (2009) is closely related to

³Browning et al. (1985) stress the importance of individual panel data for estimating a model of intertemporal labor supply.

 $^{^{4}}$ Chetty et al. (2012) represents a related literature that uses quasi-experimental evidence on individual tax changes to identify individual Marshallian or Hicksian wage-elasticities.

ours. They use a complete market setup to explore the role of 'marginal workers' when trying to measure the adjustment along the extensive margin following a wage change. Marginal workers are defined as those who are just indifferent between working and not working. Blundell et al. (2011) empirically disentangle the importance of the extensive and the intensive margin over time by disaggregating long time-series for selected European countries. They stress the role of gender and age when computing static wage-elasticities for hours worked and employment probabilities. These papers differ from each other with respect to the type and degree of worker heterogeneity, the assumed market structure, and their focus and definition of the particular margin of adjusting labor supply. They differ from ours in that they commonly use a parameterized version of a structural utility function which makes it possible to derive a functional relationship between the aggregate labor supply and aggregate wages.

We contribute to the literature on intertemporal labor supply by developing an aggregation approach for dynamic labor supply choices of heterogeneous individuals and subsequently illustrating the main components of an implied aggregate variable. Our method is novel, because it is theorybased, yet requires no specific assumptions about model parameters or distributions of explanatory variables. It simultaneously captures adjustment along the intensive and the extensive margin when anticipated wage changes hit. We then study the quantitative importance of the aggregate's various components using micro-level panel data for a particular large group of workers. These data contain information on self-reported reservation wage rates for the unemployed which are essential for estimating adjustments along the extensive margin. The panel structure helps eliminate unobserved individual fixed effects that arise in a dynamic setting.

This paper is organized as follows. Section 2 presents a dynamic model of individual labor supply under uncertainty. Section 3 develops a general aggregation procedure that features labor supply adjustment along the intensive and the extensive margin. Section 4 specifies the two econometric models used for empirical estimation, a panel data model on hours worked and a non-parametric procedure to estimate conditional densities. Section 5 presents our database and introduces the main variables used for estimation. Section 6 reports all estimation results. Section 7 concludes.

2 A Dynamic Labor Supply Model

Underlying our aggregation exercise is an individual-specific labor supply function which relates the amount of labor that an individual supplies to the market in any given period t to a set of determinants. We view this function as the outcome of an intertemporal optimization problem under uncertainty.⁵ In what follows we sketch this problem including the preferences, the constraints and the informational setting for each individual. For the sake of notational simplicity, we abstain from introducing a personspecific index until section 4.

Consider an infinitely-lived consumer. Her preferences are captured by a momentary utility function U which depends on private consumption c, leisure l, a vector of observable individual characteristics X and a vector of unobservable individual variables Z, including tastes and talents. U is assumed to be twice differentiable and strictly separable over time. Furthermore, U is strictly increasing and concave in c and h. When choosing sequences of leisure, consumption and future asset holdings to maximize her expected life-time utility, the consumer takes the real wage rate w and the real market return on assets r as given and respects the following two constraints: First, the per-period time-constraint

$$\bar{T}_t \ge l_t + h_t \tag{1}$$

which equates the available time \overline{T} to the sum of leisure and market hours worked h in each period. Second, the budget constraint

$$c_t + a_{t+1} \le w_t h_t + (1 + r_t) a_t \tag{2}$$

that sets the sum of consumption expenditures and the change in asset holdings $a_{t+1} - a_t$ equal to total earnings plus interest income from current period asset holdings a_t . A consumer starts life with initial assets a_0 .

Denoting by \mathbb{E}_t the mathematical expectation conditional on information known at the beginning of time t and by $0 < \tilde{\beta} < 1$ the discount rate,

⁵Our model exposition closely follows that in MaCurdy (1985).

the consumer's choice problem can be summarized as follows:

$$\max_{\{c_t, l_t, a_{t+1}\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \tilde{\beta}^t U(c_t, l_t; X_t, Z_t)$$
(3)

subject to equations (1), (2), the non-negativity constraints $c_t > 0$, $l_t \ge 0$, and the initial condition $a_0 > 0$.⁶ For any differentiable function $f(x_1, \ldots, x_n)$ let $\partial_{x_i} f(x_1, \ldots, x_n)$ denote the partial derivative with respect to the *i*-th component. Then, letting λ_t denote the Lagrange multiplier associated with the period *t* budget constraint, the first-order necessary conditions for utility maximization are given by:

$$\partial_c U(\cdot) - \lambda_t = 0 \tag{4a}$$

$$\partial_l U(\cdot) - \lambda_t w_t = 0 \tag{4b}$$

$$\lambda_t = \beta \mathbb{E}_t[(1 + r_{t+1})\lambda_{t+1}]. \tag{4c}$$

With the help of the implicit function theorem equations (4a) and (4b) can be solved for individual consumption and labor supply as functions of the form

$$c_t = c(w_t, \lambda_t, X_t, Z_t) \tag{5}$$

$$h_t = h(w_t, \lambda_t, X_t, Z_t). \tag{6}$$

The time-invariant functions $c(\cdot)$ and $h(\cdot)$ only depend on the specifics of the utility function $U(\cdot)$ and on whether corner solutions are optimal for hours worked in period t. These functions contain two types of arguments, namely those that capture what is going on in the current period – w_t , X_t and Z_t – and λ_t which is a sufficient statistic for past and future information relevant for the individual's current choices. If we further assume consumption and leisure to be normal goods, the concavity of the utility function implies

$$\partial_{\lambda}c < 0, \partial_{w}h \ge 0, \partial_{\lambda}h \ge 0. \tag{7}$$

⁶A complete formulation of the consumer's dynamic decision problem also requires a transversality condition for wealth: $\lim_{\tilde{T}\to\infty} \lambda_{\tilde{T}} a_{\tilde{T}} = 0.$

Equation (4c) summarizes the stochastic process governing λ_t . Assuming interest rates do not vary stochastically, this process can alternatively be expressed as an expectational difference equation:

$$\lambda_t = \tilde{\beta}(1 + r_{t+1}) \mathbb{E}_t \lambda_{t+1}.$$

Recall that any variable can be rewritten as the sum of what was expected and an expectational error ε :

$$\lambda_t = \mathbb{E}_{t-1}\lambda_t + \varepsilon_t.$$

Combining the last two expressions and solving backward yields

$$\lambda_t = \tilde{\beta}^{-t} R_t \lambda_0 + \sum_{j=0}^{t-1} \varepsilon_{t-j} \equiv \tilde{\beta}^{-t} R_t \lambda_0 + \eta_t, \qquad (8)$$

where $R_t \equiv 1/[(1+r_1)(1+r_2) \cdot \ldots \cdot (1+r_t)]$ is the common discount rate. Equation (8) nicely illustrates that apart from the sum of past expectational errors, η_t , the time-varying individual marginal utility of wealth consists of a fixed individual component λ_0 and a common time-varying component. When inserting this expression together with the consumption and labor supply function (5) and (6) into the individual life-time budget constraint which results from solving equation (2) forward, we get

$$a_0 \ge \sum_{t=0}^{\infty} R_t [c(w_t, \lambda_t, X_t, Z_t) - w_t h(w_t, \lambda_t, X_t, Z_t)].$$
(9)

Equation (9) implicitly defines λ_t . It shows that the marginal utility of consumption is a highly complex variable that depends on the initial assets, life-time wages, the market interest rate, observable and unobservable individual characteristics and preferences. For the purpose of our analysis it matters that the assumed concavity of preferences implies

$$\frac{\partial \lambda_t}{\partial a_0} < 0, \frac{\partial \lambda_t}{\partial w_t} \le 0.$$
(10)

Taken together the inequalities in (7) and (10) indicate that there exists a direct and an indirect effect of wages on hours worked. A rise in the current period's wage rate directly leads to an increase in hours worked. The indirect link exists, because a rising wage rate contributes to a rise in wealth which tends to reduce labor supply. Hence, in the intertemporal framework laid out the net effect of a change in wages on individual labor supply is unclear from a theoretical point of view.

In sum, we can express the individual labor supply function as follows:

$$h_{t} = \begin{cases} h(w_{t}, \lambda(w_{t}, \eta_{t}), X_{t}, Z_{t}) > 0 & \text{if } w_{t} \ge w_{t}^{R} \\ 0 & \text{if } w_{t} < w_{t}^{R} \end{cases}$$
$$= h(w_{t}, \lambda(w_{t}, \eta_{t}), Y_{t})I(w_{t} \ge w_{t}^{R})$$
(11)

where $I(\cdot)$ denotes the indicator function, and the vectors X_t and Z_t are combined into $Y_t = (X_t, Z_t)$ for notational convenience. The individual reservation wage rate in period t is derived from expression (4b):

$$w_t^R = \frac{\partial_l U[c_t, T, Y_t]}{\partial_c U[c_t, T, Y_t]}$$

with $(1 + r_t)a_t \ge a_{t+1}$. Equation (11) implies that the individual wage rate w_t is observed only if it is greater than or equal to the individual's reservation wage w_t^R . In general, we can think of w_t as the maximal wage rate offered.⁷

We use the labor supply function to define the individual Frisch wageelasticity:

$$\epsilon_t = \frac{\partial \log h(w, \lambda_t, Y_t)}{\partial \log w} \bigg|_{w=w_t}$$
(12a)

$$= \lim_{\Delta \to 0} \frac{\log h(w_t + \Delta, \lambda_t, Y_t) - \log h(w_t, \lambda_t, Y_t)}{\log(w_t + \Delta) - \log(w_t)}$$
(12b)

where the last equality simply follows from the definition of a derivative. This definition will prove useful in our aggregation exercise.

Frisch requires us to only consider the **direct** effects of the wage change. We compensate indirect effects due to a rise in wealth by keeping $\lambda_t = \lambda(w_t, \eta_t)$ fixed at their individual levels, instead of allowing λ_t to change

⁷We introduce the wage rate as a possibly hypothetical quantity so that we can later define a suitable population model.

with changes in w_t . Given that this elasticity abstracts from the wealth effect of a wage change, by definition it cannot become negative. In fact, ϵ_t is non-negative for stayers and zero for anyone whose offered wage falls short of the reservation wage rate. Given the dichotomous nature of the intertemporal labor supply function in equation (11), ϵ_t is not defined for individual movers who may consider changing their employment status in reaction to an incremental wage change. As we elaborate below, those movers matter in the aggregate.

3 Aggregation and the Frisch Elasticity

The derivation of the individual Frisch wage-elasticity lends itself to aggregation in a straightforward way: We replace individual working hours h_t and individual wages w_t in equation (12b) by their respective population means \overline{H}_t and \overline{W}_t .⁸

For each period t, individual working hours h_t , wage rates w_t , reservation wage rates w_t^R , as well as λ_t and Y_t are random variables with means depending on the corresponding distributions within the respective population. The mean labor supply as well as the mean wage rate received by all working individuals are given by the following two expressions:

$$\overline{H}_t = \mathbb{E}(h_t) = \int h(w, \lambda, Y) I(w \ge w^R) d\pi^t_{w, w^R, \lambda, Y},$$
(13a)

$$\overline{W}_t = \mathbb{E}(w_t) = \int w I(w \ge w^R) d\pi^t_{w,w^R}, \qquad (13b)$$

where $\pi_{w,w^R,\lambda,Y}^t$ denotes the joint distribution of the variables $(w_t, w_t^R, \lambda_t, Y_t)$ over the population and π_{w,w^R}^t stands for the marginal distribution of (w_t, w_t^R) . All other marginal distributions are written analogously. The new mean wage, $\overline{W}_t(\Delta)$, and the new mean working hours, $\overline{H}_t(\Delta)$, corresponding to the incremental wage changes are given by:

$$\overline{H}_t(\Delta) := \mathbb{E}\left(h(w_t + \Delta, \lambda_t, Y_t)I(w_t + \Delta \ge w_t^R)\right)$$

⁸Of course, we could alternatively compute the population mean of $\log h$ and $\log w$. This would slightly modify the subsequent formulae without substantially changing the analysis.

$$= \int h(w + \Delta, \lambda, Y) I(w + \Delta \ge w^R) d\pi^t_{w, w^R, \lambda, Y},$$
(14a)

$$\overline{W}_{t}(\Delta) := \mathbb{E}\left((w_{t} + \Delta)I(w_{t} + \Delta \ge w_{t}^{R})\right)$$
$$= \int (w + \Delta)I(w + \Delta \ge w^{R})d\pi_{w,w^{R}}^{t}.$$
(14b)

Inserting the various aggregates into equation (12b) yields the aggregate Frisch wage-elasticity

$$e_{t} := \lim_{\Delta \to 0} \frac{\log \overline{H}_{t}(\Delta) - \log \overline{H}_{t}}{\log \overline{W}_{t}(\Delta) - \log \overline{W}_{t}}$$
$$= \frac{\frac{\partial}{\partial \Delta} \log \overline{H}_{t}(\Delta)|_{\Delta=0}}{\frac{\partial}{\partial \Delta} \log \overline{W}_{t}(\Delta)|_{\Delta=0}} = \frac{\overline{W}_{t}}{\overline{H}_{t}} \frac{\frac{\partial}{\partial \Delta} \overline{H}_{t}(\Delta)|_{\Delta=0}}{\frac{\partial}{\partial \Delta} \overline{W}_{t}(\Delta)|_{\Delta=0}}.$$
(15)

This equation nicely illustrates that the aggregate Frisch elasticity measures changes in mean working hours in reaction to a small change of the mean wage rate.

There exists an alternative interpretation of the above definition. Mean hours worked depend among others on the distribution of wages across individuals, π_w^t . Any specific change in individual wages affects the shape of the wage distribution and therefore also the new mean hours worked and the new mean wage. One can think of many different ways in which individual wages change. Here, we consider the simplest possible wage transformation by letting the wage distribution shift by a constant $\Delta > 0$ while holding everything else constant. This corresponds to each individual facing an anticipated temporary fixed change of her wage rate w_t , so that w_t is transformed into $w_t + \Delta$ for some Δ close to zero.

In equation (15), the aggregate quantities \overline{W}_t and \overline{H}_t can be determined from observed data so that we only have to analyze the expressions $\frac{\partial}{\partial \Delta} \overline{H}_t(\Delta)|_{\Delta=0}$ and $\frac{\partial}{\partial \Delta} \overline{W}_t(\Delta)|_{\Delta=0}$. For the subsequent analysis, we denote the conditional distribution of some random variable V given a random variable W by $\pi^t_{V|W}$ and its density, if existent, by $f^t_{V|W}(\cdot)$. In particular, we will assume that the conditional distribution $\pi^t_{w^R|w}$ of w^R_t given $w_t = w$ has a continuous density $f^t_{w^R|w}(\cdot)$. We require that the marginal distribution π^t_w of w_t also possesses a continuous density $f^t_w(\cdot)$.

Let us first consider the simpler term $\overline{W}_t(\Delta)$ which, for $\Delta > 0$, quantifies the new mean wage rate paid by employers. Note that for a working individual her new wage rate simply is $w_t + \Delta$, and hence $\frac{\partial}{\partial\Delta}(w_t + \Delta)|_{\Delta=0} = 1$. This is not generally true at the aggregate level. The point is that for $\Delta > 0$ we consider the increase in the mean wage rate for the entire labor force and not only for the subpopulation of employed workers. The transformation implies that a wage rate $w_t + \Delta$ is offered to an unemployed individual, but the actual wage rate paid will remain zero if $w_t + \Delta < w_t^R$. On the other hand, there exist marginal workers who do not work at a wage rate w_t , but may decide to work at a higher wage rate $w_t + \Delta$. More precisely, by (14b) we have

$$\overline{W}_{t}(\Delta) = \int (w+\Delta)I(w \ge w^{R})d\pi^{t}_{w,w^{R}} + \int (w+\Delta)I(w^{R} \in [w,w+\Delta])d\pi^{t}_{w,w^{R}} d\Phi) = \int (w+\Delta)I(w \ge w^{R})d\pi^{t}_{w,w^{R}} + \int (\nu+\Delta)\left(\int_{\nu}^{\nu+\Delta} f^{t}_{w^{R}|\nu}(\tilde{\nu})d\tilde{\nu}\right)f^{t}_{w}(\nu)d\nu$$

Taking derivatives yields

$$\frac{\partial}{\partial \Delta} \overline{W}_t(\Delta)|_{\Delta=0} = \underbrace{\int I(w \ge w^R) d\pi^t_{w,w^R}}_{EPR_t} + \underbrace{\int \nu f^t_{w^R|\nu}(\nu) f^t_w(\nu) d\nu}_{\tau^{ext}_{w,t}}.$$
 (17)

The first term EPR_t corresponds to the employment ratio in period t, i.e., the fraction of the population employed. EPR_t enters here because the wage change relates to all employees whereas the change in the mean wage is computed by summing over the entire population. The second term is due to changes in mean earnings with respect to employment adjustment along the extensive margin. For a given wage rate w the term $wf_{w^R|w}^t(w)$ quantifies the rate of increase of wages to be paid to marginal workers if w increases by $\Delta > 0$. $\tau_{w,t}^{ext}$ is the mean of these rates over all wages, $\tau_{w,t}^{ext} = \mathbb{E}(w_t f_{w^R|w_t}^t(w_t))$.

Necessarily $\tau_{w,t}^{ext} \geq 0$, and one typically expects that $\tau_{w,t}^{ext} > 0$. To simplify the argument consider the case where w_t^R and w_t are independent such that $f_{w^R|w}^t \equiv f_{w^R}^t$ does not depend on w and is equal to the marginal density of reservation wages.⁹ Then $\tau_{w,t}^{ext} > 0$ if for some wage rate ν with

⁹The micro model implies that reservation wages are variables which do not depend on actual wages paid or offered. Therefore it does not seem implausible to assume that the random variables w_t^R and w_t are independent. However, there may exist an indirect link due to correlations with common explanatory variables such as education, for example. Highly educated individuals tend to have higher reservation wages than

 $f_w^t(\nu) > 0$ we also have $f_{w^R}^t(\nu) > 0$. In other words, $\tau_{w,t}^{ext} > 0$ if there exists some overlap between the support of the distributions of wages w_t and the support of the distribution of reservation wages w_t^R . This will typically be fulfilled for any real economy.

Let us now analyze the term $\overline{H}_t(\Delta)$ which, for $\Delta > 0$, quantifies the new mean working hours. Similar to (16) we obtain

$$\overline{H}_{t}(\Delta) = \int h(w + \Delta, \lambda, Y) I(w \ge w^{R}) d\pi^{t}_{w, w^{R}, \lambda, Y}$$

$$+ \int h(w + \Delta, \lambda, Y) I(w^{R} \in [w, w + \Delta]) d\pi^{t}_{w, w^{R}, \lambda, Y},$$
(18)

where the second term quantifies the part of the change of \overline{H}_t which is due to the fact that if wage rates rise from w_t to $w_t + \Delta$, then the subpopulation of all individuals with reservation wage rates $w_t^R \in [w_t, w_t + \Delta]$ will contribute non-zero working hours. Using $\partial_w h(w, \lambda, Y)$ to denote the partial derivative of h with respect to w, the derivative of the first term simply is $\mathbb{E}(\partial_w h(w_t, \lambda_t, Y_t)I(w_t \ge w_t^R))$. Calculating the derivative of the second term is slightly more complicated. A rigorous analysis can be found in Appendix A. We then arrive at the following expression:

$$\frac{\partial \overline{H}_{t}(\Delta)}{\partial \Delta}\Big|_{\Delta=0} = \underbrace{\int \partial_{w} h(w,\lambda,Y) I(w \ge w^{R}) d\pi^{t}_{w,w^{R},\lambda,Y}}_{\tau^{int}_{h,t}} + \underbrace{\int \mathbb{E}\left(h_{t}| \ w^{R}_{t} = w_{t} = \nu\right) f^{t}_{w^{R}|\nu}(\nu) f^{t}_{w}(\nu) d\nu}_{\tau^{ext}_{h,t}}.$$
(19)

The first term $\tau_{h,t}^{int}$ quantifies the average derivatives of the individual functions h for the subpopulation \mathcal{E}_t of all individuals already working at wage rate w_t . Put differently, $\tau_{h,t}^{int}$ measures the total labor supply adjustment along the intensive margin. It can also be interpreted as a weighted mean of individual Frisch elasticities for the subpopulation \mathcal{E}_t . Recall that individual Frisch elasticities are given by $\epsilon_t = \frac{\partial \log h(w,\lambda_t,Y_t)}{\partial \log w} \bigg|_{w=w_t} = \partial_w h(w_t,\lambda,Y) \frac{w_t}{h_t}$.

others and they are likely to receive higher wage offers. This may introduce a correlation between w_t^R and w_t over the population. Our procedure for estimating $\tau_{w,t}^{ext}$ described in section 4 takes such effects into account.

Therefore,

$$\tau_{h,t}^{int} = \int_{\mathcal{E}_t} \partial_w h(w,\lambda,Y) d\pi_{w,w^R,\lambda,Y}^t = \mathbb{E}_{\mathcal{E}_t}(\partial_w h(w_t,\lambda_t,Y_t)) = \mathbb{E}_{\mathcal{E}_t}\left(\epsilon_t \frac{h_t}{w_t}\right),$$
(20)

where $\mathbb{E}_{\mathcal{E}_t}(\cdot)$ is used to denote expected values over all individuals in \mathcal{E}_t . Since usually $\mathbb{E}_{\mathcal{E}_t}(\epsilon_t \frac{h_t}{w_t}) \neq \mathbb{E}_{\mathcal{E}_t}(\epsilon_t) \frac{\overline{H}_t}{\overline{W}_t}$, we cannot emphasize enough that $\frac{\overline{W}_t}{\overline{H}_t} \tau_{h,t}^{int}$ in equation (21) below does **not** correspond to a simple mean of individual elasticities over \mathcal{E}_t .

The second term $\tau_{h,t}^{ext} \geq 0$ captures all adjustments of working hours along the extensive margin, i.e., all changes due to transitions between unemployment and employment. Its interpretation is analogous to that of $\tau_{w,t}^{ext}$ already discussed above. Note that $\mathbb{E}(h_t | w_t^R = w_t = w)$ is the average number of hours a marginal worker with reservation wage rate $w_t^R = w$ intends to work if she is offered the wage rate $w_t = w$. For a given wage rate w the term $\mathbb{E}(h_t | w_t^R = w_t = w) f_{w^R | w}^t(w)$ quantifies the rate of change of hours worked by marginal workers if w changes.

To sum up, the aggregate Frisch wage-elasticity is given by¹⁰

$$e_t = \frac{\overline{W}_t}{\overline{H}_t} \left(\frac{\tau_{h,t}^{int} + \tau_{h,t}^{ext}}{EPR_t + \tau_{w,t}^{ext}} \right).$$
(21)

The quantities \overline{W}_t , \overline{H}_t and EPR_t can be determined directly from realworld data. Contrary to what we observed for the individual wage-elasticity, the aggregate Frisch wage-elasticity explicitly takes into account the behavior of marginal workers. In fact, the size of the extensive margins of adjustment crucially depends on the relative size of this group of workers. We will capture their behavior using reservation wage data for unemployed workers who are willing to work at a given wage. We measure the total adjustment along the intensive margin by looking at employed workers who change hours on the job in reaction to a wage shock.

¹⁰Most existing work in business cycle analysis is based on models which assume timeinvariant wage elasticities of labor supply. At a first glance it may come as a surprise that aggregate elasticities determined by (21) explicitly depend on time. Time dependence of e_t is an inevitable consequence of the fact that all major determinants vary over time, albeit at a high degree of persistence.

4 Econometric Modeling

We will describe next an econometric approach to estimating the total labor supply adjustment in order to quantify the aggregate Frisch wage-elasticity. The estimation of the total adjustment consists of two independent steps. First, we measure adjustment along the intensive margin using a standard Panel model of labor supply for stayers. Then we quantify adjustment along the extensive margin with a non-parametric approach for movers.

For a given period t, the expression for the total labor supply adjustment along the intensive margin from equation (19) can be estimated via its sample equivalent

$$\hat{\tau}_{h,t}^{int} = \frac{1}{N_t^w} \sum_{i: h_{it} > 0} \partial_w \hat{h}(w_{it}, \lambda_{it}, Y_{it})$$
(22)

where N_t^w denotes the employed workers in period t in our sample. The determinants of the individual labor supply $h_{it} = h(w_{it}, \lambda_{it}, Y_{it})$ $I(w_{it} \ge w_{it}^R)$ are given by the wage rate w_{it} , the marginal utility of wealth λ_{it} , observable individual characteristics X_{it} and unobservable random factors Z_{it} . We closely follow the empirical literature on male labor supply analysis where hours worked are treated as a continuous variable. Assuming that all determinants have a linear effect on the individual labor supply we get the following panel data model:¹¹

$$\log h_{it} = \gamma_0 + \gamma_1 \log w_{it} + (X_{it})' \beta + \lambda_{it} + z_{it}, \qquad (23)$$

where X_{it} is a vector of p different observable attributes and the p-dimensional parameter vector β captures their influence on the individual labor

$$\begin{aligned} \lambda_{it} w_{it} &= \exp(-X'_{it}\beta^* - z^*_{it})\sigma h^{\sigma-1}_{it} \\ \log \lambda_{it} + \log w_{it} &= -X'_{it}\beta^* - z^*_{it} + \log \sigma + (\sigma - 1)\log h_{it} \\ \log h_{it} &= (\sigma - 1)^{-1}(-\log \sigma + \log w_{it}) + X'_{it}\beta + \tilde{\lambda}_{it} + \tilde{z}_{it}, \end{aligned}$$

with $\beta = (\sigma - 1)^{-1} \beta^*$, $\tilde{\lambda}_{it} = (\sigma - 1)^{-1} \log \lambda_{it}$ and $\tilde{z}_{it} = (\sigma - 1)^{-1} z_{it}^*$.

¹¹Note that if we assumed the utility function to be separable between leisure and consumption, linearity would directly follow. Let $U = f(c_{it}, Z_{it}) - \exp(-X'_{it}\beta^* - z^*_{it})(T - l_{it})^{\sigma}$ as in MaCurdy (1985) where β^* is a vector of parameters associated with the observable individual characteristics X_{it}, z^*_{it} is the contribution of the unmeasured characteristics and $\sigma > 1$ is a preference parameter common to all individuals. Then, the first order condition (4b) reads as follows and can be reformulated further:

supply. The term z_{it} measures the influence of unobservable individual characteristics. For the sake of our aggregation exercise we need to measure the hours' reaction of employed workers to a small anticipated wage change. Standard labor supply analysis typically is interested in statements on individual labor supply in the context of the entire labor force, and hence selection may matter. Selection plays no role in our analysis, because we focus on changes in aggregate labor supply: Only the employed workers matter for the intensive margin in the aggregate. Even if we estimated the panel data model on the entire labor force, γ_1 would not correspond to the aggregate Frisch wage-elasticity, since γ_1 is relevant for employed workers only. The respective wage-elasticity for those who remain unemployed is always zero, and the group of marginal workers serves to determine the extensive margins of adjustment in the aggregate.

In order to retrieve the individual fixed components of λ_{it} and z_{it} we decompose their sum into their respective time averages, individual averages, and a residual:

$$\lambda_{it} + z_{it} = \underbrace{\lambda_i + z_i}_{\mu_i} + \underbrace{\lambda_t + z_t}_{\mu_t} + \underbrace{\lambda_{it} - \lambda_i - \lambda_t + z_{it} - z_i - z_t}_{\xi_{it}}.$$
 (24)

This yields

$$\log h_{it} = \gamma_0 + \gamma_1 \log w_{it} + (X_{it})' \beta + \mu_i + \mu_t + \xi_{it}, \qquad (25)$$

where the errors ξ_{it} may be heteroskedastic. Therefore, we use Whiterobust standard errors in our estimation procedure. Since the individual wage rate is correlated with the marginal utility of wealth λ_{it} which enters the error term, we instrument for wage rates. The structure of the panel model above as well as the instrumental variable (IV) approach are in accordance with the setup commonly used in the literature estimating the individual labor supply of males (cf. for example Blundell and MaCurdy (1999)). The instruments must be uncorrelated with the timevarying wealth and preference component of the error, i. e., $\lambda_{it} - \lambda_i - \lambda_t$ and $z_{it} - z_i - z_t$. However, they may correlate with the individual fixed effects. We estimate equation (25) using a fixed-effect estimator. In order to guarantee identification of β , there may not be a constant in X and none of the observable attributes may be determined by the wage rate, so that the matrix $\mathbb{E}\{[X - \mathbb{E}[X|\log w]][X - \mathbb{E}[X|\log w]]'\}$ be positive definite. As is common in this literature, the sum over all individual effects is standardized to equal zero.

The panel data model implies that an estimate of the derivative of the individual labor supply function with respect to the wage rate is given by

$$\partial_w \hat{h}(w_{it}, \lambda_{it}, Y_{it}) = \frac{h_{it}}{w_{it}} \hat{\gamma}_1,$$

so that for each period t the total labor supply adjustment along the intensive margin can be estimated by

$$\hat{\tau}_{h,t}^{int} = \frac{1}{N_t^w} \sum_{i: h_{it} > 0} \frac{h_{it}}{w_{it}} \hat{\gamma}_1.$$
(26)

Let us now consider the adjustments along the extensive margin. To maintain a high degree of generality, we take a non-parametric estimation approach. Recall from equations (17) and (19) that $\tau_{w,t}^{ext}$ and $\tau_{h,t}^{ext}$ are given by

$$\tau_{w,t}^{ext} = \int \nu f_{w^R|\nu}^t(\nu) f_w^t(\nu) d\nu$$
(27)

and

$$\tau_{h,t}^{ext} = \int \mathbb{E}\left(h_t | w_t^R = w_t = \nu\right) f_{w^R|\nu}^t(\nu) f_w^t(\nu) d\nu, \qquad (28)$$

respectively. Therefore, for given ν we have to find estimates for the product of densities $f_{w^R|\nu}^t(\nu)f_w^t(\nu) = f_{w^R,w}^t(\nu,\nu)$ and the conditional expectation $\mathbb{E}(h_t| w_t^R = w_t = \nu)$. As the joint distribution of reservation wages and hourly wage rates cannot be observed, we condition on observable individual characteristics, X, to estimate the product of densities

$$f_{w^{R},w}^{t}(w_{1},w_{2}) = \int f_{w^{R},w|X}^{t}(w_{1},w_{2})d\pi_{X}^{t}$$

$$= \int f_{w^{R}|X}^{t}(w_{1})f_{w|X}^{t}(w_{2})d\pi_{X}^{t}.$$
(29)

and assume independence of the wage and the reservation wage condi-

tional on individual characteristics. This implies that the joint density of the wage and the reservation wage can be factorized conditional on individual characteristics.¹² Both densities as well as the conditional expectation are estimated nonparametrically, resulting in $\hat{f}_{w^R|X}^t(\cdot)$, $\hat{f}_{w|X}^t(\cdot)$ and $\hat{\mathbb{E}}(h_t| w_t^R = w_t = \cdot)$, respectively. We employ a two-step conditional density estimator and consider first two simple regression models, followed by a nonparametric kernel density estimator to determine an estimate from the residuals of the regression models. For the estimation of the conditional expectation we employ a local constant kernel estimator, also referred to as the Nadaraya-Watson kernel estimator.¹³ For each period t, $\tau_{w,t}^{ext}$ and $\tau_{h,t}^{ext}$ can then be approximated by

$$\hat{\tau}_{w,t}^{ext} = \int \nu \left(\frac{1}{N_t} \sum_{i} \hat{f}_{w^R|X=X_{it}}^t(\nu) \hat{f}_{w|X=X_{it}}^t(\nu) \right) d\nu \tag{30}$$

and

$$\hat{\tau}_{h,t}^{ext} = \int \hat{\mathbb{E}} \left(h_t | w_t^R = w_t = \nu \right) \left(\frac{1}{N_t} \sum_i \hat{f}_{w^R | X = X_{it}}^t(\nu) \hat{f}_{w | X = X_{it}}^t(\nu) \right) d\nu$$
(31)

where N_t denotes the sum of employed and unemployed individuals in period t in our sample. This allows us to estimate the aggregate Frisch wage-elasticity as specified in equation (21) for any period t.

5 Data

Our empirical work is based on data from the German Socio-Economic Panel (SOEP), a representative sample of private households and individuals living in Germany. The panel was started in 1984 (wave A) and has been updated annually through 2013 (wave BD). The panel design closely follows that of the Panel Study of Income Dynamics (PSID) – a representa-

¹²This assumption is comparable to what Hall and Mueller (2015) call "proportionality-to-productivity hypothesis" which states that individual reservation wage rates and actual wage rates are proportional to the individual productivity.

¹³The nonparametric estimation procedure for $\hat{f}_{w^R|X}^t(\cdot)$, $\hat{f}_{w|X}^t(\cdot)$ and $\hat{\mathbb{E}}(h_t|w_t^R = w_t = \cdot)$ is described in Appendix B (see e.g. Li and Racine (2006)).

tive sample of US households and individuals – but also takes idiosyncrasies of the German legal and socio-economic framework into account.¹⁴ Since 2000, the SOEP covers on average 12,000 households and 20,000 individuals per year. A set of core questions is asked every year, including questions on education and training, labor market behavior, earnings, taxes and social security, etc.

We use the SOEP, because we consider it particularly well suited for the purpose of our analysis. It is one of the few micro panels currently available that contain indirect information on reservation wage rates of unemployed workers. This variable is essential for our effort to quantify changes in a worker's decision to move between employment and unemployment. Apart from detailed information on individual characteristics, the SOEP also reports an employed individual's market hours worked and earnings. We can thus compute an individual's hourly wage rate.

5.1 Sample

For the sake of our empirical analysis we need consistent data on individual labor market behavior for a large group over a rather long time horizon. Therefore, we focus on the working age population of German males living in former West Germany who are between 25 and 64 years old. We do so, because we are neither interested in the peculiarities of women's working behavior nor in the institutional differences between former East and West Germany. Including females in a relatively long panel study would be problematic because in Germany, unlike in many other countries, females have undergone severe changes in their labor market behavior during the past decades and are less attached to the workforce than elsewhere. Since we want to focus on those who actively participate in the labor market, we exclude retirees, individuals in military service under conscription or in community service which can serve as substitute for compulsory military service, and individuals currently undergoing education. We also exclude individuals with missing information on unemployment experience or the amount of education or training. A maximum of 77 individuals is affected.

 $^{^{14}}$ A detailed description of the panel's design, its coverage, the main questions asked, etc. is contained in the *Desktop Companion* to the SOEP, which is accessible online at www.diw.de.

Our sample ranges from 2000 to 2013. That is because in 2000 a refreshment sample was added to the SOEP which effectively doubled the number of observations.

At any point in time we distinguish between employed and unemployed workers. The unbalanced panel of working individuals varies between 3,911 and 1,837 observations. We use these individuals whenever we compute measures related to employed workers. For all questions related to unemployment we consider individuals who are not employed and have answered the question on reservation wages. This leaves us with 64 to 140 individuals between 2000 and 2013.¹⁵

5.2 Variables

Our key variables of interest are the hourly wage rate and actual working hours for the employed, the reservation wage rate for the unemployed, and individual characteristics.¹⁶ A person's total hours worked, h_{it} , are given by the average actual weekly working hours. There is a wide range of answers to the question "And how much on average does your actual working week amount to, with possible overtime?" – answers range from 5.5 to 80 hours per week. In fact, the distribution of h_{it} is not discrete in nature, but quite dispersed, in particular during the last 15 to 20 years. It seems that the traditional 40 hours workweek gradually loses its prevalence as there are increasing possibilities of part-time work, higher skilled workers are asked to work more, and more flexible work options have become available.¹⁷

The hourly wage rate is calculated by dividing the current net monthly earnings by the product of 4.3 and contractual weekly working hours. We use net earnings, since information on the reservation wage is only available in net terms and we need the wage rate, w_{it} , and the reservation wage rate to be comparable. We convert all nominal values into real ones by dividing all nominal expressions by the consumer price index which uses 2010 as base year.

 $^{^{15}}$ A detailed description of our sample is given in Appendix C. In particular, Table 6 shows summary statistics and we list all refinements to the original data.

¹⁶A list of all SOEP variables with respective names as well as a list of all generated variables with description is given in Appendix C.

 $^{^{17}\}mathrm{Histograms}$ of actual hours worked for the years 2000, 2005, 2010 and 2012 are available in Figure 3 in Appendix C.

The reservation wage is generated from answers to the question "How much would the net pay have to be for you to consider taking the job?" which is posed to all individuals who are not in gainful employment or in military service and who intend to take up a job in the future. The associated working hours are deduced from the variable "Interest in full or part-time work". We assume persons answering the question "Are you interested in full- or part-time employment?" with "Full-time employment", "Either" or "Don't know" to be interested in 40 hours of work per week. We assign 20 hours of work per week to those who indicate an interest in "Part-time employment". The reservation wage rate corresponds to the ratio of the monthly net reservation earnings to the product of 4.3 and desired weekly working hours. Since the year 2007 the SOEP contains detailed information on desired weekly working hours. If available we use the answer to the question "In your opinion how many hours a week would you have to work to earn this net income?" to calculate the reservation wage. In fact, we can use this more detailed information to check whether attributing 20 and 40 hours work per week is reasonable. Table 1 indicates that for individuals who are indifferent or those interested in full-time work the assumed 40 hours of work per week for the years prior to 2007 are a reasonable choice. For the years 2007, 2009, 2011 and 2013, around 86 % of those individuals believe that they would have to work between 35 and 45 hours to earn the desired reservation net income. For individuals interested in part-time work the picture is not as clear. Part-time work is usually any work with less than 30 to 35 hours per week, but in a legal sense is defined as employment with fewer hours than a comparable full-time job. This vague definition is reflected in the relative frequencies of the number of working hours associated with the reservation net earnings in Table 1. However, note that for all years few individuals fall into this category, in fact at most 11 individuals. Therefore, for the years prior to 2007 we stick to the assumption of 20 working hours per week for individuals interested in part-time work.

Given that our reservation wages are derived from self-reported information, we check for their reliability and plausibility. We do so by constructing the ratio of an unemployed worker's reservation wage and her most recent available wage rate. Feldstein and Poterba (1984) argue that

Warra	Full	-time, Ei	ther, Don	't know		Pa	art-time	
Wave	N	[0, 35)	[35, 45]	(45,70]	N	[0, 15)	[15, 25]	(25, 40]
2007	111	0.05	0.85	0.11	11	0.00	0.64	0.36
2009	133	0.05	0.86	0.1	11	0.00	0.36	0.64

0.13

0.07

9

8

0.22

0.00

0.33

0.25

0.44

0.75

2011

2013

64

55

0.06

0.02

0.81

0.91

Table 1: Preferred Working Hours Linked to Reservation Net Income[%]

Notes: N denotes the number of observations for West German males aged 25 to 64 with answers "Full-time", "Either", "Don't know" and "Part-time", respectively, to the question "Are you interested in full- or part-time employment?".

this ratio negatively affects a worker's acceptance probability of future job offers. The plot of the logarithm of this ratio for selected years is contained in Figure 4 in Appendix C. This logarithmic ratio is roughly symmetrically distributed around zero with a lot of mass centered around zero. Hence, we have no reason to doubt that our reservation wage measures what it is supposed to measure, namely a worker's willingness to accept a suitable wage offer.

We use different individual characteristics for the employed and the unemployed. For the sake of estimating our panel model, we consider as individual characteristics of the employed a dummy for the family status (1 if married or currently living in dwelling with steady partner, 0 otherwise), work experience in full-time employment, and three dummy variables on the occupational group. Each working individual belongs to one out of the following four occupational groups. The first group comprises employees in agriculture, animal husbandry, forestry, horticulture or in mining. The second group comprises employees in manufacturing or technical occupations (e.g. engineers, chemists, technicians). All employees in the service industry belong to the third group. The fourth group comprises all other workers, in particular persons who do not report an established profession or workers without any further specification of their professional activity.

We use an IV approach to account for the possible endogeneity of hourly wage rates. We use as instruments men's unemployment rates which vary across region ("Raumordnungsregionen") and time together with work experience in full-time employment squared. The regionally varying unemployment rates by gender are available until 2012 from IAB, the Institute of Employment Research at the German Bureau of Labor Statistics in Nuremberg. Effectively, a "Raumordnungsregion" corresponds to a city and its surrounding countryside. There is a total of 75 regions in former West-Germany. This is the only disaggregated level at which both SOEP data and data from the IAB are available. A high unemployment rate tends to exert downward pressure on wage rates; it is strongly inversely linked to labor demand and, thus, can help identify labor supply.¹⁸ Regarding the second instrument, it is well known from empirical work that work experience is a crucial determinant of individual wage rates. We formally test for the relevance and the validity of our instruments and report test results in section 6.

The determinants of the reservation wage which are needed for the estimation of the conditional density $f_{w^R|X}^t(\cdot)$ are given by unemployment experience in years, a dummy on whether or not information for unemployment benefits is provided, the size of unemployment benefits, and a dummy for highly qualified individuals. The latter group has obtained a college or university degree.¹⁹ Note that in each year individuals are asked about the size of the unemployment benefits in the previous year so that the information about unemployment benefits is not available for the last wave, i.e. 2013. For estimating $f_{w|X}^t(\cdot)$ we use schooling, work experience in full-time employment, and work experience squared. The schooling variable is based on the number of years of education or training undergone and exhibits some variation over time. It includes secondary vocational education and ranges from 7 to 18 years.

¹⁸As an alternative, we considered public investment expenditures that directly affect labor demand and inversely covary with unemployment. They also vary across regions and time. We decided against it, because many regions stopped collecting this information beyond 2008. The first stage estimation results for the overlapping years were qualitatively comparable to what we report below.

¹⁹These determinants of the reservation wage rate are in line with the literature as Prasad (2004) and Addison et al. (2009), among others, find that duration of joblessness, availability and level of unemployment compensation and observables of education or skill level are the most important determinants of reservation wages.

6 Results

We start this section by presenting results from the panel, density and conditional expectation estimation needed for the determination of the total adjustments along the intensive and extensive margin, respectively. Then, we provide results for the aggregate Frisch wage-elasticity of labor supply.

6.1 Panel model estimation

For calculating the total labor supply adjustment along the intensive margin $\tau_{h,t}^{int}$, we first have to estimate the panel data model for the working population. We start with estimating it for the unbalanced panel of working-age men.²⁰ We do a two-stage least squares panel estimation to address the possibility that workers' hourly wage rates are endogeneous. We consider as instruments men's regional unemployment rates and their actual work experience squared. Good instruments need to be relevant and valid. In the first stage, we check for the relevance of these two instruments and find work experience squared and men's unemployment rate to be negatively correlated with wage rates. While the correlation for work experience squared is strongly significant, the one for men's unemployment rate is significant at the five percent level only. Other highly significant variables included in the first-stage regression are work experience, the family status, the fourth occupational group and the constant. Wage rates rise in work experience gathered. However, the coefficient on work experience squared is negative, so that each further increase in experience conveys a progressively smaller increase in the wage rate. We implement the Kleibergen and Paap (2006) test for weak identification. The corresponding Wald F-statistic equals 171.75. This value clearly exceeds the critical value of 19.93 that Stock and Yogo (2005) give for one endogeneous regressor and two instruments at the 10% significance level. We therefore reject the null hypothesis of weak instruments.

Table 2 shows estimation results for the panel model in equation (25). For the benchmark specification, i.e. the IV approach, the constant and the coefficients on the logarithm of the wage rate and work experience each are

 $^{^{20}{\}rm We}$ also estimate this model on a balanced panel of continuously employed males and report results in Appendix E.

(a) With IVs (Benchmark)		(b) W	(b) Without IVs		
$\log h$	Coef.	$\log h$	Coef.		
log w	0.4967896^{***}	log w	-0.1820386***		
FAMILY	0.0103898	FAMILY	0.0652104^{***}		
EXPFT	0.0220621^{***}	EXPFT	0.0395073^{***}		
O1	0.0578375^{**}	O1	0.0524363		
O3	0.0097194	O3	-0.0044778		
O4	-0.0352537^{***}	O4	-0.0803268***		
CONST	2.180711***	CONST	3.561831***		

Table 2: Results for the Panel Model Estimation

Notes: ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively. FAMILY, EXPFT, O1, O3, O4 and CONST represent the family status dummy variable, work experience in years, dummy variables on occupational group and a constant, respectively. The sample underlying the estimation is described in section 5. Results for the time-fixed effects are not reported. They can be received from the authors upon request.

strongly significantly positive. Moreover, the hours of workers in agricultural occupations positively deviate from those in the reference group O2, whereas the hours of workers in the residual category deviate negatively. The parameter estimate of the logarithm of the wage rate equals .50. This estimate corresponds to the average wealth-compensated individual wage elasticity of labor supply which has received a lot of attention in the empirical labor literature. Our estimate for working age males in Germany is in line with what is commonly reported in that literature. Table 2b shows that neglecting the endogeneity of wage rates leads to a negative point estimate on the logarithm of the hourly wage rate.²¹

In addition to checking whether or not our two instruments are relevant, we also need to check for their validity. We do so by using a Hansen-Sargan overidentification test. The corresponding Chi-sq(1) statistic has a p-value of .8358, suggesting that we cannot reject the null that the instruments are exogeneous. Taken together, the outcome of the Kleibergen-Paap test and the Hansen-Sargan test indicates that the reported estimate is consistent. Lastly, we check whether the hourly wage rates are endogenous at all by performing a Hausman (1978) test for model misspecification. The corresponding T-statistic equals 391.75 and has a p-value very close to zero.

²¹This feature is also discussed in Reynaga and Rendon (2012).

We interpret this as evidence in support of the the null hypothesis that IV estimation is the correct procedure.

6.2 Conditional Density and Expectation Estimation

Wave	CONST	SCHOOL	EXPFT	EXPFT2	N
2000	-7.930915***	1.211615^{***}	0.562846^{***}	-0.00945361^{***}	3,911
2001	-8.090481***	1.327943^{***}	0.451627^{***}	-0.00758881^{***}	3,819
2002	-5.151546	1.063008^{***}	0.575499^{***}	-0.0107573^{**}	3,516
2003	-7.269173***	1.157287^{***}	0.553718^{***}	-0.00889634^{***}	3,336
2004	-8.282064***	1.221461^{***}	0.601881^{***}	-0.00972103^{***}	3,186
2005	-8.742367***	1.223459^{***}	0.570326^{***}	-0.00857869^{***}	3,003
2006	-8.745768***	1.205416^{***}	0.588400^{***}	-0.00929423^{***}	3,180
2007	-8.419527***	1.219177^{***}	0.502950^{***}	-0.00734845^{***}	3,094
2008	-8.646421***	1.242763^{***}	0.486372^{***}	-0.00710784^{***}	2,923
2009	-9.654023***	1.295408^{***}	0.532449^{***}	-0.00798240^{***}	2,960
2010	-7.640216***	1.223868^{***}	0.426812^{***}	-0.00653955^{***}	2,772
2011	-8.445578***	1.274699^{***}	0.430801^{***}	-0.00594328^{***}	2,312
2012	-10.17785***	1.388722^{***}	0.490151^{***}	-0.00732412^{***}	1,972
2013	-9.567012***	1.292689^{***}	0.543793^{***}	-0.00852420^{***}	1,837

Table 3: Results for Wage Regression, Equation (B.32)

Notes: See Table 2. CONST, SCHOOL, EXPFT and EXPFT2 denote a constant, the schooling variable, work experience, and work experience squared, respectively. N denotes number of observations.

As described in section 4 and in Appendix B we have to first estimate the wage and reservation wage regression, equation (32) and (33), to get the conditional densities $\hat{f}_{w|X}^t(\cdot)$ and $\hat{f}_{w^R|X}^t(\cdot)$, respectively. Regression results are shown in Table 3 and 4.

For all years except for 2002 the coefficients on the individual characteristics as well as the constant are highly significant. Hourly wage rates rise in the years of schooling and in work experience gathered. However, the coefficient on work experience squared is negative, so that each further increase in experience conveys a progressively smaller increase in the wage rate.

For the estimation of equation (33) we have between 64 and 140 observations. The constant is highly significant between 8.17 and 11.11. The coefficient on the unemployment duration is mostly negative and not significant. The predominant sign of the coefficient is in line with predictions from theoretical models and empirical evidence that the reservation wage

Wave	CONST	EXPUE	UEBEN	HQD	UEBEND	N
2000	9.966150***	-0.0770586	0.00183397	1.618011	-2.573844^{*}	121
2001	9.192752^{***}	-0.188597^{*}	0.00335740^{***}	3.084474^{***}	-2.719694^{**}	115
2002	10.60007^{***}	-0.196065^*	0.00301913^{**}	0.868946	-3.393103^{**}	134
2003	10.02087***	-0.0638434	0.00355757^{***}	3.848668^{***}	-4.204844^{***}	140
2004	11.11624^{***}	-0.211025^{*}	0.00195311^*	1.434982	-3.696272^{***}	135
2005	9.297777^{***}	-0.152008	0.00575854^{***}	4.006034^{**}	-5.598096^{**}	126
2006	9.626797^{***}	-0.256564^{**}	0.00512546^{***}	4.891392^{***}	-4.694982^{**}	131
2007	8.982358***	-0.114566	0.00374094^{***}	3.791119^{***}	-4.367064^{***}	118
2008	9.298201***	0.115917	0.00531788	0.925121	-5.766371	91
2009	8.920629***	0.0193379	0.00612451^*	3.767985	-4.022587	141
2010	8.166092^{***}	-0.0361239	0.00234985^{**}	2.085710^{***}	-1.577844	136
2011	10.92151^{***}	-0.208675	0.00502359^*	2.320921	-6.731472^{**}	67
2012	8.253459^{***}	-0.0539062	0.00294721	4.587710	1.107611	68

Table 4: Results for Reservation Wage Regression, Equation (B.33)

Notes: See Table 2. CONST, EXPUE, UEBEN, HQD and UEBEND denote a constant, unemployment experience in years, unemployment benefits in 100 euros, a dummy for highly qualified individuals and one on whether information on unemployment benefits is provided, respectively. N denotes number of observations. We can generate results through 2012 only, since the information on the size of unemployment benefits always pertains to *last year*.

decreases with waiting time for a new job.²² The reservation wage rate significantly decreases if unemployed individuals receive unemployment benefits, but it increases in the level of those benefits. Being a highly qualified individual, i.e. having obtained a college or university degree, increases the reservation wage, in many years significantly.

The resulting conditional densities $f_{w|X}^t(\cdot)$ and $f_{w^R|X}^t(\cdot)$ vary with individual characteristics $X = X_{it}$. Therefore, we restrict our analysis to the densities conditional on mean individual characteristics, i.e. $X_{it} = \bar{X}_t$. Note that this choice is rather arbitrary. We could also consider results for median or prespecified individual characteristics. Figure 1 shows the lower quartile, the median and the upper quartile for the wage as well as the reservation wage distribution conditional on mean individual characteristics. It does not come as a surprise that the distribution of the reservation wage lies to the left of the wage distribution for all years as individuals are only working if the offered wage exceeds the reservation wage. For the wage distribution, the lower quartile, the median and the upper quartile vary around 10.3, 12.9 and 15.8, respectively. For 2002 the distribution is more

 $^{^{22}}$ See, e.g., Krueger and Mueller (2016).

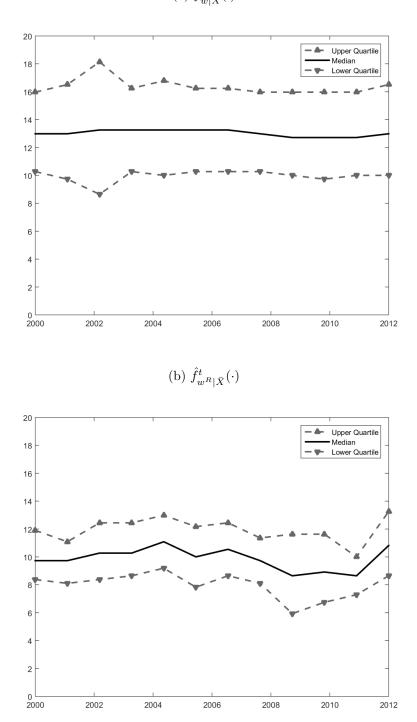
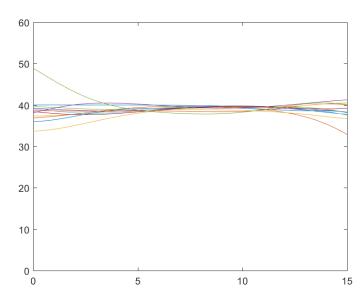


Figure 1: Quartiles of the densities conditional on $X=\bar{X}$ (a) $\hat{f}^t_{w|\bar{X}}(\cdot)$

Notes: The horizontal axes measure years and the vertical axes represent the wage rate (a) and the reservation wage rate (b), respectively. This figure shows the lower quartile, the median and the upper quartile of the conditional densities $\hat{f}^t_{w|\bar{X}}(\cdot)$ and $\hat{f}^t_{w^R|\bar{X}}(\cdot)$, respectively.

dispersed which is possibly also one reason for the less accurate regression results in this year. On the other hand, for the reservation wage distribution, the lower quartile, the median and the upper quartile vary around 7.7, 9.5 and 11.4, respectively. Starting in 2004, the distribution begins to shift to the left – a process that is not reversed until 2011. This shift coincides with the beginning of the Hartz-reforms that led to a decrease of the mean size of unemployment benefits.

Figure 2: Expectation of weekly working hours conditional on $w = w^R$



Notes: The horizontal axis measures the real hourly wage rate and the vertical axis represents working hours. This figure shows the regression functions for the conditional expectation $\hat{\mathbb{E}}(h_t | w_t^R = w_t)$ for the years 2000 to 2013.

In the following, we consider results from the conditional expectation estimation generated by considering the reservation wage w^R and associated hours data h^R for each year. Figure 2 shows the nonparametric regression results for all years. The expectation corresponds to the hours a marginal worker would work at her reservation wage. Therefore, the estimated values of around 40 working hours per week seem plausible.

6.3 The Aggregate Frisch Wage-Elasticity of Labor Supply

For the calculation of the aggregate Frisch elasticity we determine the employment ratio EPR_t , the mean labor supply \overline{H}_t as well as the mean wage rate \overline{W}_t received by all working individuals directly from observed data (see Table 7 in Appendix D). Results for the estimated determinants of the aggregate Frisch wage-elasticity, i.e. $\hat{\tau}_{h,t}^{int}$, $\hat{\tau}_{h,t}^{ext}$ and $\hat{\tau}_{w,t}^{ext}$ are shown in Table 8 in Appendix D, whereas results for the aggregate Frisch wage-elasticity

$$\begin{split} \hat{e}_t &= \frac{\overline{W}_t}{\overline{H}_t} \left(\frac{\hat{\tau}_{h,t}^{int} + \hat{\tau}_{h,t}^{ext}}{EPR_t + \hat{\tau}_{w,t}^{ext}} \right) \\ &= \underbrace{\frac{\overline{W}_t}{\overline{H}_t} \frac{1}{EPR_t + \hat{\tau}_{w,t}^{ext}} \cdot \hat{\tau}_{h,t}^{int}}_{\hat{\tau}_{h,t}^{int}} + \underbrace{\frac{\overline{W}_t}{\overline{H}_t} \frac{1}{EPR_t + \hat{\tau}_{w,t}^{ext}} \cdot \hat{\tau}_{h,t}^{ext}}_{\hat{\tau}_{h,t}^{ext}}. \end{split}$$

and its weighted components $\tilde{\tau}_{h,t}^{int}$ and $\tilde{\tau}_{h,t}^{ext}$ are shown in Table 5. The aggregate Frisch elasticity ranges between .85 and 1.06. In fact, except for the years 2009 and 2010 that immediately followed the outbreak of the Great Recession, the aggregate Frisch elasticity varies very little between .85 and .87. The larger value of 1.06 in 2009 is caused by the higher hours adjustment along the intensive margin, i.e. a higher value of $\tilde{\tau}_{h,t}^{int}$ in 2009 compared to the other years. In almost all years, the aggregate reaction of hours worked can be attributed roughly equally to the weighted hours' adjustment of stayers and movers.

7 Conclusion

This paper illustrates the power and the importance of taking aggregation seriously when thinking about an explicit bridge between individual measures related to intertemporal labor supply and corresponding aggregates for large groups. We do so in an environment that features uncertainty and optimizing workers who differ in their preferences, income, wealth, and labor market status. Our aggregation approach is novel in that it is theory-based, yet does not rely on a particular preference structure or

117	^	$\tilde{\tau}_{t}^{int}$	$\tilde{\tau}_{l}^{ext}$
Wave	\hat{e}_t	n,t	n,t
2000	0.86	0.43	0.44
	(0.02)	(0.02)	(0.01)
2001	0.87	0.44	0.43
	(0.02)	(0.03)	(0.02)
2002	0.85	0.46	0.39
	(0.02)	(0.04)	(0.03)
2003	0.86	0.42	0.44
	(0.02)	(0.02)	(0.01)
2004	0.86	0.42	0.44
	(0.03)	(0.02)	(0.01)
2005	0.86	0.43	0.43
	(0.02)	(0.02)	(0.01)
2006	0.86	0.44	0.42
	(0.02)	(0.02)	(0.01)
2007	0.86	0.42	0.44
	(0.02)	(0.02)	(0.01)
2008	0.85	0.48	0.38
	(0.02)	(0.03)	(0.04)
2009	1.06	0.66	0.40
	(0.19)	(0.19)	(0.02)
2010	0.92	0.47	0.45
	(0.01)	(0.01)	(0.01)
2011	0.85	0.43	0.42
	(0.02)	(0.02)	(0.02)

Table 5: The Aggregate Frisch Wage-Elasticity and Weighted Components

Notes: The sample as described in section 5 underlies the determination of the aggregate Frisch wage-elasticity \hat{e}_t . The confining series is men's unemployment rate which is available through 2012 only. Bootstrapped standard errors are in parantheses (1,000 replications).

distributional assumptions for explanatory variables. Moreover, it simultaneously allows for labor supply adjustment along the intensive and the extensive margin. We use the Frisch wage-elasticity of labor supply – a key concept for policy analysis – as our organizing principle. Aggregation introduces non-linearities which drive a wedge between the mean of individual elasticities and their aggregate counterpart. The size of this wedge varies with the shape of the distribution of actual wages, reservation wages and hours worked as well as with the size of the group of marginal workers. The aggregation procedure presented is general and flexible enough to be in principle applicable to alternative theories of labor supply and also to a full-fledged macroeconomic analysis if the group considered comprises the entire population.

The paper also illustrates the practical usefulness of our approach with information on males at working-age living in former West-Germany between 2000 and 2013. For an unbalanced panel, we find that aggregation yields a Frisch elasticity that can be up to twice as large as the individual elasticity. Also, the extensive and the intensive margin are roughly equally important for the total variation in hours work. For a balanced panel, aggregation triples the size of the individual Frisch elasticity and the extensive margin outweighs the intensive one. This latter result is consistent with a central finding of the labor supply literature summarized in Blundell and MaCurdy (1999) that the extensive margin matters most for explaining variation in total person hours over the business cycle.

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Appendix A Formal derivation of the derivative of equation (18), second term

We obtain

$$\int h(w + \Delta, \lambda, Y) I(w^R \in [w, w + \Delta]) d\pi^t_{w, w^R, \lambda, Y}$$

=
$$\int \int \int h(w + \Delta, \lambda, Y) d\pi^t_{(\lambda, Y)|(w^R, w)} I(w^R \in [w, w + \Delta]) d\pi^t_{w^R|w} d\pi^t_w$$

=
$$\int \left(\int_{\nu}^{\nu + \Delta} \mathbb{E} \left(h(w_t + \Delta, \lambda_t, Y_t) | w_t^R = \tilde{\nu}, w_t = \nu \right) f^t_{w^R|\nu}(\tilde{\nu}) d\tilde{\nu} \right) f^t_w(\nu) d\nu.$$

In what follows we assume the conditional expectation $\mathbb{E}\left(h(w_t+\Delta, \lambda_t, Y_t)|w_t^R = \tilde{\nu}, w_t = \nu\right)$ as well as $f_{w^R|\nu}^t(\tilde{\nu})$ to be continuous functions of ν and $\tilde{\nu}$. Also note that $\mathbb{E}\left(h(w_t, \lambda_t, Y_t)|w_t^R = w_t = \nu\right) = \mathbb{E}\left(h_t|w_t^R = w_t = \nu\right)$. The mean value theorem then implies that for all ν there exist a $\xi_{\nu} \in [\nu, \nu + \Delta]$ such that

$$\begin{split} &\int \left(\int_{\nu}^{\nu+\Delta} \mathbb{E} \left(h(w_t + \Delta, \lambda_t, Y_t) | \ w_t^R = \tilde{\nu}, w_t = \nu \right) f_{w^R|\nu}^t(\tilde{\nu}) d\tilde{\nu} \right) f_w^t(\nu) d\nu \\ &= \int \Delta \mathbb{E} \left(h(w_t + \Delta, \lambda_t, Y_t) | \ w_t^R = \xi_{\nu}, w_t = \nu \right) f_{w^R|\nu}^t(\xi_{\nu}) f_w^t(\nu) d\nu \\ &= \Delta \int \mathbb{E} \left(h_t | \ w_t^R = w_t = \nu \right) f_{w^R|\nu}^t(\nu) f_w^t(\nu) d\nu \\ &+ \Delta \int \left(\mathbb{E} \left(h(w_t + \Delta, \lambda_t, Y_t) | \ w_t^R = \xi_{\nu}, w_t = \nu \right) f_{w^R|\nu}^t(\xi_{\nu}) \\ &- \mathbb{E} \left(h(w_t, \lambda_t, Y_t) | \ w_t^R = w_t = \nu \right) f_{w^R|\nu}^t(\nu) \right) f_w^t(\nu) d\nu. \end{split}$$

Obviously, for all ν ,

$$\left| \mathbb{E} \Big(h(w_t + \Delta, \lambda_t, Y_t) | \ w_t^R = \xi_{\nu}, w_t = \nu \Big) f_{w^R | \nu}^t(\xi_{\nu}) - \mathbb{E} \Big(h(w_t, \lambda_t, Y_t) | \ w_t^R = w_t = \nu \Big) f_{w^R | \nu}^t(\nu) \right| \to 0$$

as $\Delta \to 0$. Therefore,

$$\frac{\partial}{\partial \Delta} \int h(w + \Delta, \lambda_t, Y) I(w^R \in [w, w + \Delta]) d\pi^t_{w, w^R, \lambda, Y} \bigg|_{\Delta = 0}$$

$$= \lim_{\Delta \to 0} \frac{\int h(w + \Delta, \lambda_t, Y) I(w^R \in [w, w + \Delta]) d\pi^t_{w, w^R, \lambda, Y}}{\Delta}$$
$$= \int \mathbb{E} \left(h_t | w_t^R = w_t = \nu \right) f^t_{w^R | \nu}(\nu) f^t_w(\nu) d\nu.$$

Appendix B Conditional density and expected hours estimation

In order to approximate $\tau_{h,t}^{ext}$ and $\tau_{w,t}^{ext}$ we need to first estimate the conditional densities $f_{w|X}^t(\cdot)$ and $f_{w^R|X}^t(\cdot)$ as well as the conditional expectation $\mathbb{E}(h_t| w_t^R = w_t = \cdot).$

For the density estimation, we employ a two-step conditional density estimator and consider first the following two simple regression models for each period t and individuals i with positive (reservation) wage rate

$$w_{it} = \alpha_{t0} + \sum_{j=1}^{p} \alpha_{tj} X_{it,j} + \delta_{it}, \quad i = 1, \dots, N_t^w,$$
(32)

$$w_{it}^{R} = \alpha_{t0}^{R} + \sum_{j=1}^{p} \alpha_{tj}^{R} X_{it,j} + \delta_{it}^{R}, \quad i = 1, \dots, N_{t}^{R}$$
(33)

where N_t^w denotes the number of wage observations in period t, N_t^R denotes the number of reservation wage observations in period t, $\alpha_t = (\alpha_{t0}, \ldots, \alpha_{tp})'$ and $\alpha_t^R = (\alpha_{t0}^R, \ldots, \alpha_{tp}^R)'$ are of dimension $(p + 1 \times 1)$ and X_{it} is a vector of p different observable attributes. We assume that the distributions of the random terms δ_{it} and δ_{it}^R are independent of X_{it} and calculate estimates $\hat{\alpha}_t$ as well as residuals $\hat{\delta}_{it} = w_{it} - \hat{\alpha}_{t0} - \sum_{j=1}^p \hat{\alpha}_{tj} X_{it,j}$ and $\hat{\alpha}_t^R$ as well as $\hat{\delta}_{it}^R = w_{it}^R - \hat{\alpha}_{t0}^R - \sum_{j=1}^p \hat{\alpha}_{tj}^R X_{it,j}$, respectively.

Let $f_{\delta}^t(f_{\delta^R}^t)$ denote the density of the error terms $\delta_{it}(\delta_{it}^R)$ over the population. Then, on the one hand $f_{w|X=X_{it}}^t(w_2) = f_{\delta}^t(w_2 - \alpha_{t0} - \sum_{j=1}^p \alpha_{tj}X_{it,j})$ and we use a nonparametric kernel density estimator to determine an estimate \hat{f}_{δ} from the residuals $\{\hat{\delta}_{it}\}_{i=1}^{N_t^w}$ of regression model (33), on the other hand $f_{w^R|X=X_{it}}^t(w_1) = f_{\delta^R}^t(w_1 - \alpha_{t0}^R - \sum_{j=1}^p \alpha_{tj}^R X_{it,j})$ and we use a nonparametric kernel density estimator to determine an estimate \hat{f}_{δ^R} from the residuals $\{\hat{\delta}_{it}^R\}_{i=1}^{N_t^R}$ of regression model (32):

$$\hat{f}_{w|X=X_{it}}^{t}(\cdot) = \frac{1}{N_{t}^{w} b w_{t}^{w}} \sum_{j=1}^{N_{t}^{w}} k \left(\frac{\hat{\delta}_{jt} - (\cdot - \hat{\alpha}_{t0} - \sum_{l=1}^{p} \hat{\alpha}_{tl} X_{it,l})}{b w_{t}^{w}} \right)$$
$$\hat{f}_{w^{R}|X=X_{it}}^{t}(\cdot) = \frac{1}{N_{t}^{R} b w_{t}^{w^{R}}} \sum_{j=1}^{N_{t}^{R}} k \left(\frac{\hat{\delta}_{jt}^{R} - (\cdot - \hat{\alpha}_{t0}^{R} - \sum_{l=1}^{p} \hat{\alpha}_{tl}^{R} X_{it,l})}{b w_{t}^{w^{R}}} \right)$$

where $k(\cdot)$ is a standard normal kernel and the bandwidths $bw_t^{w^R}$ and bw_t^w are chosen according to the normal reference rule-of thumb, i.e.

$$\begin{aligned} k(v) &= \frac{1}{\sqrt{2\pi}} \cdot \exp\left(-\frac{1}{2}v^2\right), \\ bw_t^w &= 1.06 \cdot \sigma_{\delta_t} \cdot \left(N_t^w\right)^{-1/5} \quad \text{and} \quad bw_t^{w^R} = 1.06 \cdot \sigma_{\delta_t^R} \cdot \left(N_t^R\right)^{-1/5}, \end{aligned}$$

with σ_{δ_t} $(\sigma_{\delta_t^R})$ being the standard deviation of the error terms δ_{it} (δ_{it}^R) in period t.

For the estimation of the conditional expectation $\mathbb{E}(h_t | w_t^R = w_t = \cdot)$ we employ a local constant kernel estimator, also referred to as the Nadaraya-Watson kernel estimator (cf. Nadaraya (1964) and Watson (1964)). We use the reservation wage w^R as explanatory variable and associated desired working hours h^R as dependent variable to account for the condition $w_t^R = w_t$. This leads to

$$\hat{\mathbb{E}}\left(h_{t} \mid w_{t}^{R} = w_{t} = \nu\right) = \frac{\int h^{R} \hat{f}_{h^{R}, w^{R}}^{t}(\nu, h^{R}) dh^{R}}{\hat{f}^{t}(\nu)} = \frac{\sum_{i=1}^{N_{t}^{R}} h_{it}^{R} \cdot k\left(\frac{w_{it}^{R} - \nu}{bw^{\mathbb{E}}}\right)}{\sum_{i=1}^{N_{t}^{R}} k\left(\frac{w_{it}^{R} - \nu}{bw^{\mathbb{E}}}\right)},$$
(34)

where $bw^{\mathbb{E}}$ denotes the bandwidth and is calculated as follows. We use local constant least squares cross-validation with leave-one-out kernel estimator to calculate the smoothing parameter for each year. Then, the bandwidth $bw^{\mathbb{E}}$ is the average over all smoothing parameters.

Appendix C Data

C.1 SOEP Samples

Each household and thereby each individual in the SOEP is part of one of the following samples:

- Sample A: 'Residents in the FRG', started 1984
- Sample B: 'Foreigners in the FRG', started 1984
- Sample C: 'German Residents in the GDR', started 1990
- Sample D: 'Immigrants', started 1994/95
- Sample E: 'Refreshment', started 1998
- Sample F: 'Innovation', started 2000
- Sample G: 'Oversampling of High Income', started 2002
- Sample H: 'Extension', started 2006
- Sample I: 'Incentivation', started 2009

C.2 SOEP Variables

Variable Name	Variable Lable
\$SAMREG	Current wave sample region
PSAMPLE	Sample member
SEX	Gender
GEBJAHR	Year of birth
\$POP	Sample membership
\$NETTO	Current wave survey status
LABNET\$\$	Monthly net labor income
\$TATZEIT	Actual weekly working hours
\$VEBZEIT	Agreed weekly working hours
\$UEBSTD	Overtime per week
STIB\$\$	Occupational Position
Y11101\$\$	Consumer price index
e.g. DP170	Amount of necessary net income
e.g. AP20	Interest in full or part-time work
e.g. XP19	Number of hours for net income
EXPFT\$\$	Working experience full-time employment
EXPUE\$\$	Unemployment experience
KLAS\$\$	StaBuA 1992 Job Classification
ISCED\$\$	Highest degree/diploma attained
\$FAMSTD	Marital status in survey year
e.g. DP9201	Currently have steady partner
e.g. HP10202	Partner lives in household
\$BILZEIT	Amount of education or training (in years)
\$P2F03	Amount of monthly unemployment insurance
\$P2G03	Amount of monthly unemployment assistance

C.3 SOEP Variable Refinements

- Actual weekly working hours: When the value for the variable actual weekly working hours is missing, we use instead, if available, agreed weekly working hours and, if available, add overtime per week.
- Agreed weekly working hours: When the value for the variable agreed weekly working hours is missing, we use instead, if available, actual weekly working hours and, if available, subtract overtime per week.
- Amount of necessary net income: For the years 1984 to 2001 DM-values are converted to euros by dividing the respective DM-values by 1.95583.

C.4 Sample

Sample Definition	Condition			
Only private households	keep if $POP=1 \lor POP=2$			
Only successful interviews	keep if NETTO \in			
	$\{10, 12, 13, 14, 15, 16, 18, 19\}$			
No first time interviewed persons aged	drop if NETTO=16			
17				
Male population	drop if $SEX=2$			
West Germany	drop if SAMPREG=2			
Age	drop if AGE $< 25 \lor AGE > 64$			
Exclusion of retirees	drop if STIB=13			
Exclusion of individuals in military ser-	drop if STIB=15			
vice under conscription or in commu-				
nity service as substitute for compul-				
sory military service				
Exclusion of individuals that are cur-	drop if STIB=11			
rently in education				
Individuals from sample A, E, F, H, I	drop if PSAMPLE $\in \{2, 3, 4, 7\}$			
No individuals with missing informa-	drop if BILZEIT < 0			
tion				
	drop if EXPUE < 0 and $h = 0$			

C.5 Descriptive Statistics

	Employed			Unemployed With w^R -obs.				
Wave	2000	2005	2010	2013	2000	2005	2010	2013
Observations	3911	3003	2772	1837	121	126	136	64
Age [yrs.]	42.26	43.58	45.44	46.38	41.73	42.09	44.15	45.70
Schooling completed [yrs.]	12.43	12.58	12.82	12.94	11.15	11.11	11.24	11.22
Work experience [yrs.]	19.77	20.57	21.97	22.25	16.61	16.49	16.82	18.05
Married or cohabiting [%]	0.82	0.81	0.80	0.81	0.68	0.78	0.69	0.56
High-skilled [%]	0.24	0.24	0.28	0.29	0.12	0.10	0.14	0.14
Employed in O1	0.02	0.02	0.02	0.02	-	-	-	-
Employed in O2	0.43	0.40	0.37	0.38	-	-	-	-
Employed in O3	0.54	0.54	0.56	0.59	-	-	-	-
Duration of unempl. [yrs.]	-	-	-	-	2.90	3.54	3.94	5.18
Entitled to unempl. benefits [%]	-	-	-	-	0.60	0.29	0.26	0.00

Table 6: Summary Statistics of Our Sample

Notes: O1 represents workers employed in agriculture and related fields. O2 stands for employment in manufacture or technical occupations. O3 measures employment in services. The sample of employees is used for the panel model estimation, the sample of unemployed workers with reservation wage observation is used for the estimation of the extensive margins of adjustment. A detailed description of all variables is given in section 5.

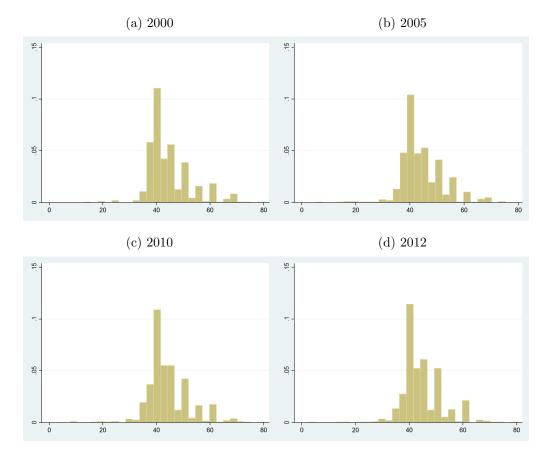
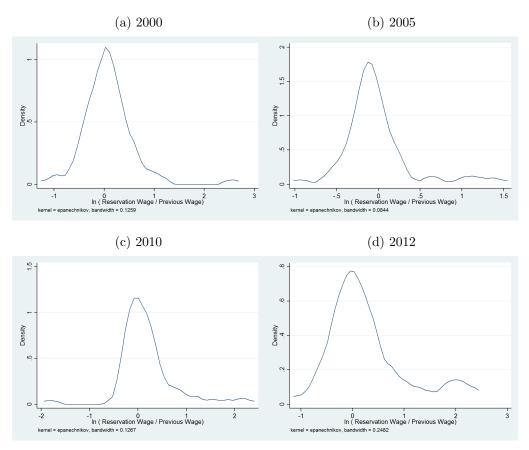


Figure 3: Histograms of Actual Weekly Hours Worked

Figure 4: Job Seekers' Reservation Wage Rate Relative to Most Recent Wage



Appendix D Results for the Unbalanced Panel

117	TT	TT 7	
Wave	H_t	W_t	EPR_t
2000	44.21	13.30	0.97
2001	44.09	13.53	0.97
2002	43.91	14.10	0.96
2003	43.64	13.73	0.96
2004	43.58	14.16	0.96
2005	43.77	13.76	0.96
2006	44.21	13.68	0.96
2007	44.24	13.52	0.96
2008	44.02	13.38	0.97
2009	43.97	13.53	0.96
2010	43.42	13.42	0.95
2011	43.73	13.73	0.97
2012	43.68	14.10	0.97

Table 7: Means of Hours Worked, Wages, and Employment Ratios

Notes: The employment ratio EPR_t is computed by dividing the number of working individuals by the total sample size in each period t.

Wave	$\hat{\tau}_{h,t}^{int}$	$\hat{\tau}_{h,t}^{ext}$	$\hat{\tau}_{w,t}^{ext}$
2000	2.21	2.26	0.90
	(0.05)	(0.12)	(0.02)
2001	2.17	2.11	0.88
	(0.05)	(0.19)	(0.02)
2002	2.08	1.82	0.84
	(0.04)	(0.30)	(0.02)
2003	2.09	2.21	0.85
	(0.04)	(0.13)	(0.02)
2004	2.04	2.12	0.83
	(0.04)	(0.11)	(0.02)
2005	2.09	2.10	0.85
	(0.04)	(0.12)	(0.02)
2006	2.20	2.12	0.89
	(0.05)	(0.10)	(0.02)
2007	2.14	2.20	0.87
	(0.04)	(0.13)	(0.02)
2008	2.21	1.77	0.90
	(0.06)	(0.27)	(0.02)
2009	3.02	1.84	1.23
	(0.86)	(0.17)	(0.35)
2010	2.15	2.06	0.87
	(0.04)	(0.10)	(0.02)
2011	2.14	2.12	0.87
	(0.05)	(0.16)	(0.02)

Table 8: Estimated Components of the Aggregate Frisch Elasticity

Notes: Bootstrapped standard errors are in parantheses (1,000 replications). The confining series is men's unemployment rate which is available through 2012 only.

Appendix E Results for the Balanced Panel

Our fixed-effect estimation procedure requires the time index t to converge to infinity to ensure consistent estimates of the individual fixed effects. Therefore, we create a balanced panel from our sample which includes those working males who are continuously employed over the sample period. Our balanced panel comprises 841 individuals. The balanced panel is more selective in its composition than the unbalanced panel. Thus, it should not come as a surprise that the intensive margin hours adjustment in reaction to a wage change is smaller than for the unbalanced panel. Our estimate of the aggregate Frisch wage-elasticity is very close to what Pistaferri (2003) reports for married men at prime working-age in Italy between 1989 and 1993.

Table 9: Results for the Panel Model Estimation

(a) With IVs (Benchmark)

(b) Without IVs

	. ,		
$\log h$	Coef.	$\log h$	Coef.
log w	0.201738***	log w	-0.1405153***
FAMILY	-0.0042555	FAMILY	0.0224449**
EXPFT	0.0096702^{***}	EXPFT	0.0142749
O1	-0.0180731	O1	-0.614608
O3	0.0134911*	O3	0.0123609
O4	0.0169549	O4	0.0282236
CONST	3.109609***	CONST	3.882037***

Notes: ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively. FAMILY, EXPFT, O1, O3, O4 and CONST represent the family status dummy variable, work experience in years, dummy variables on occupational group and a constant, respectively. The sample underlying the estimation is described in section 5. Results for the time-fixed effects are not reported. They can be received from the authors upon request.

Wave	\hat{e}_t	$\tilde{\tau}_{h,t}^{int}$	$\tilde{\tau}_{h,t}^{ext}$
2000	0.61	0.17	0.44
	(0.01)	(0.01)	(0.01)
2001	0.60	0.18	0.43
	(0.02)	(0.01)	(0.02)
2002	0.58	0.18	0.39
	(0.02)	(0.02)	(0.03)
2003	0.61	0.17	0.44
	(0.01)	(0.01)	(0.01)
2004	0.61	0.17	0.44
	(0.02)	(0.01)	(0.01)
2005	0.60	0.17	0.43
	(0.01)	(0.01)	(0.01)
2006	0.60	0.18	0.42
	(0.01)	(0.01)	(0.01)
2007	0.61	0.17	0.44
	(0.01)	(0.01)	(0.01)
2008	0.57	0.19	0.38
	(0.03)	(0.01)	(0.04)
2009	0.67	0.27	0.40
	(0.08)	(0.08)	(0.02)
2010	0.64	0.19	0.45
	(0.01)	(0.01)	(0.01)
2011	0.60	0.17	0.42
	(0.02)	(0.01)	(0.02)

Table 10: The Aggregate Frisch Wage-Elasticity and Weighted Components

Notes: For the determination of the aggregate Frisch wage-elasticity \hat{e}_t we consider the sample as described in section 5. Bootstrapped standard errors are in parantheses (1,000 replications). The confining series is men's unemployment rate which is available through 2012 only.

Wave	$\hat{ au}_{h,t}^{int}$	$\hat{ au}_{h,t}^{ext}$	$\hat{\tau}_{w,t}^{ext}$
2000	0.90	2.26	0.90
	(0.02)	(0.12)	(0.02)
2001	0.88	2.11	0.88
	(0.02)	(0.19)	(0.02)
2002	0.84	1.82	0.84
	(0.02)	(0.30)	(0.02)
2003	0.85	2.21	0.85
	(0.02)	(0.13)	(0.02)
2004	0.83	2.12	0.83
	(0.02)	(0.11)	(0.02)
2005	0.85	2.10	0.85
	(0.02)	(0.12)	(0.02)
2006	0.89	2.12	0.89
	(0.02)	(0.10)	(0.02)
2007	0.87	2.20	0.87
	(0.02)	(0.13)	(0.02)
2008	0.90	1.77	0.90
	(0.02)	(0.27)	(0.02)
2009	1.23	1.84	1.23
	(0.35)	(0.17)	(0.35)
2010	0.87	2.06	0.87
	(0.02)	(0.10)	(0.02)
2011	0.87	2.12	0.87
	(0.02)	(0.16)	(0.02)

Table 11: Estimated Components of the Aggregate Frisch Elasticity

Notes: Bootstrapped standard errors are in parantheses (1,000 replications). The confining series is men's unemployment rate which is available through 2012 only.

Wave	\overline{H}_t	\overline{W}_t	EPR_t
2000	44.30	13.44	0.99
2001	43.99	14.49	0.99
2002	44.18	14.19	0.98
2003	43.98	14.43	0.97
2004	44.18	14.38	0.99
2005	44.16	14.60	0.98
2006	44.55	14.69	0.99
2007	44.97	14.62	0.99
2008	44.89	14.34	1.00
2009	44.71	14.81	0.99
2010	44.02	14.95	0.99
2011	44.47	15.13	0.98
2012	44.33	15.03	0.99

Table 12: Means of Hours Worked, Wages, and Employment Ratios

Notes: The employment ratio EPR_t is computed by dividing the number of working individuals by the total sample size in each period t.