



Essays on Public and Private Insurance of Income Shocks

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Thesis submitted for assessment with a view to obtaining the degree
of Doctor of Economics of the European University Institute

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Abstract

This thesis explores issues related to public and private insurance of income shocks, and the importance of human capital accumulation.

The first chapter argues that the intertemporal elasticity of substitution of labor supply (*i.e.s.*) is a state-dependent variable which strongly depends on the return to human capital accumulation. Estimating a life cycle model I find that the average *i.e.s.* is low (0.35), and comparable with micro estimates, even in the presence of human capital. However, the average *i.e.s.* hide important heterogeneity: for college graduates the *i.e.s.* more than doubles over the life cycle, whereas it increases by about 58 percent for workers without a college degree.

The second chapter argues that heterogeneous returns to human capital accumulation affects the degree to which search effort of unemployed deviates from the socially optimal level, and the reason behind the deviation. I find that (i) the main social costs associated with unemployment insurance are not due to moral hazard problems, but are due to distortionary effects of labor income taxes needed to finance the insurance. (ii) The magnitude of the moral hazard problem and the tax distortion problem, differs substantially by age and education. And, (iii) the degree of tax progressiveness and benefit regressiveness has important effects on the deviation of search effort.

The third chapter study the relation between co-movement of income shocks and precautionary asset holdings. If households perceive spousal labor supply as an insurance mechanism, it is evident that this mechanism should work better the lower the co-movement of income shocks. We find that (i) households in which both spouses have the same education level or work in the same industry have a higher correlation of income shocks compared to couples with different education/industry. And, (ii) households who face larger co-movements of income shocks hold larger precautionary buffers.

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Introduction

This thesis explores issues related to the role of public and private insurance of income shocks, and the importance of human capital accumulation.

The first chapter focuses mainly on the role of human capital accumulation in explaining labor supply decisions. In this chapter I offer new insights on the intertemporal elasticity of substitution of labor supply (*i.e.s.*) both at a theoretical and an empirical level. I first show that within a standard life cycle model of labor supply featuring human capital accumulation, the *i.e.s.* is a state-dependent variable which strongly depends on the return to human capital accumulation. I identify two important sources of heterogeneity w.r.t. return to human capital accumulation: age and education. Second, I argue that the average *i.e.s.* is low and comparable with micro estimates, even in the presence of human capital. Estimating the life cycle model for two different education groups; workers with and without a college degree, I find that the average *i.e.s.* in the sample is 0.35. However, the average *i.e.s.* hide important heterogeneity: for college graduates the *i.e.s.* more than doubles over the life cycle, whereas it increases by about 58 percent for workers without a college degree. Moreover, young workers without a college degree have 32 percent higher *i.e.s.* than young college graduates. Finally, I find that the welfare costs of permanent tax changes are much lower than previously found in models with human capital.

The second chapter focuses on the effects of public insurance of unemployment uncertainty, taking into account that workers have different returns to labor market experience. In particular, I argue that it is important to take into account heterogeneous returns to labor market experience when analyzing both the degree to which search effort of unemployed deviates from the socially optimal level, and the reason behind the deviation. Whereas the moral hazard problem traditionally has been viewed as the main cost associated with UI, the presence of a career-effect substantially increases the social costs associated with tax distortions, which are created by the need to finance the UI. Using a life cycle model featuring heterogeneous returns to labor market experience and costly search effort of unemployed, I measure the degree to which search effort deviates from the socially (constrained) optimal level, and the relative importance of the moral hazard problem and the tax distortion problem. The three main findings are: (*i*) the main social costs associated with today's US unemployment insurance are not due to moral hazard problems, but are due to the distortionary effects of labor income taxes needed to finance the insurance. (*ii*) The magnitude

of the *moral hazard problem* and the *tax distortion problem*, differs substantially over the life cycle and across education groups. And, (iii) the degree of tax progressiveness and benefit regressiveness has important effects on the deviation of search effort from the optimal level.

In the third chapter, we focus on the role of spousal labor supply as a source of insurance against labor income uncertainty. The chapter takes a first step towards a better understanding of the nature of income risk that different households face by studying the relation between co-movement of income shocks and precautionary asset holdings. If households perceive spousal labor supply as an insurance mechanism, it is evident that this mechanism should work better the lower the co-movement in shocks to the spousal incomes. Thus, if the household is using labor supply to smooth shocks we should see that the correlation of shocks to the spouses' wages matters for precautionary wealth accumulation, independent of the variance of the joint wage processes. We test this prediction empirically using administrative data from Norway. First, we document that households in which both spouses have the same education level or are working in the same industry have a higher correlation of income shocks than couples that have different education levels and work in different industries. Second, we show that households who face larger co-movements of income shocks hold larger precautionary buffers. More specifically, we find that an increase from the lowest to the highest correlation documented in our sample would predict a median increase in financial assets of 97,144 NOK, or equivalently 16 percent of yearly disposable income.

1 Human Capital and the State-Dependent Intertemporal Elasticity of Substitution

1.1 Introduction

Over the last decades substantial effort has been devoted to estimating the intertemporal elasticity of substitution for labor supply (*i.e.s.*). The *i.e.s.* plays a crucial role in both the public finance literature and in the real business cycle literature, as it describes how individuals shift labor supply across periods in response to tax changes and wage changes. Moreover, it governs the life cycle labor supply decision. The *i.e.s.* describes both how labor supply changes along the expected wage profile, and how labor supply responds to unexpected shifts in the wage profile.

In this paper I show, both theoretically and empirically, that the intertemporal elasticity of substitution of labor with respect to transitory wage changes is not constant across the population nor is it constant throughout an individual's working-life. In particular, the *i.e.s.* is a state-dependent variable that depends crucially on worker's return to labor market experience, henceforth referred to as human capital. When workers accumulate human capital through labor supply, return to labor is the sum of contemporaneous wages and the discounted future gains in wages. The larger is the (discounted) future gains in wages relative to contemporaneous wages, the smaller is the response of labor supply to changes in contemporaneous wages. Thus, workers with a high return to human capital accumulation will have a lower intertemporal elasticity of substitution compared to workers with a low return to human capital accumulation.

I identify two important sources of heterogeneity with respect to the return to human capital accumulation; age and education. Age, and in particular years left until retirement, is important as it determines how long workers will benefit from an increase in human capital. Moreover, it is plausible that production of human capital becomes more difficult with age. As a result, the *i.e.s.* will increase with age. Looking at cohort averages of real wage profiles taken from the Current Population Survey (CPS), from age 23 to age 45, where wages typically starts to level off, it seems evident that there are large differences in the return to human capital accumulation across education groups: real wages increases by 27 percent for individuals with less than High School, 42 percent for High School graduate, 70 percent for workers with some

This chapter has benefitted from comments from seminar participants at the 2012 EEA conference, the 7th Nordic Summer Symposium in Macroeconomics, the University of Oslo and Norges Bank.

College education, and finally 137 percent for College graduates.¹ As the *i.e.s.* is decreasing in the return to human capital accumulation, it will decrease with education.

A second contribution of the paper is to draw attention on the sample used to estimate the *i.e.s.*. There is an important distinction to be made between voluntary and involuntary quits. This is because involuntary quits are not a choice by the worker, and should therefore not be included in the measure of labor supply when estimating the *i.e.s.*. I show that the majority of unemployment spells are involuntary; The share of voluntary transitions from employment to unemployment are less than 20 percent for young college graduates and about 15 percent for young workers without a college degree, according to monthly data on labor market transitions taken from the CPS data set. From age 30 and onwards, the shares of voluntary quits are even lower. Moreover, one must be cautious with respect to changes in labor supply due to sample selection, in particular changes in the share of students. I show that most of the sharp increase in the extensive margin, measured as no. of weeks worked during a year, between age 20 and age 25 is due to a significant reduction in weeks of unemployment, and an increase in the no. of weeks worked due to students leaving university and starting to work throughout the year. Whether or not these changes are included in the measure of labor supply matter significantly for the estimate of the *i.e.s.*. This is because the main changes in labor supply comes from the extensive margin and occurs early in life, when the increase in wages is strongest. Ideally, one should then control for all workers who are involuntarily unemployed and all workers who switch from being a student to working during a survey year. However, when this is not possible, I argue that it is better to only include the intensive margin as a measure of optimal labor supply. This implies that the *i.e.s.* estimates refers to the intertemporal elasticity of the intensive-margin only.²

To quantify the importance of the state-dependency of the *i.e.s.* and the empirical measure of labor supply, I estimate a life cycle model with endogenous labor supply along the intensive margin, human capital accumulation through learning by doing and wage uncertainty, using cohort data on white males from CPS for workers with and without a college degree. As emphasized by [Blundell and MaCurdy \(1999\)](#), the primary method of estimating the *i.e.s.* in the presence of human capital is to use a structural model. The individuals return to human capital accumulation is not observable, and as shown below, when wages depend on the endogenous stock of human capital, the *i.e.s.* is no longer a constant but a function of several variables and parameters.

First, I find that the *i.e.s.* is low, with a population average of 0.35, and comparable with micro estimates, even in the presence of human capital accumulation. A vast micro literature has estimated the *i.e.s.* assuming that wages are exogenous to the hours decision, and typically find an estimate of the *i.e.s.* in the range (0 – 0.5). (See e.g. [MaCurdy \(1981\)](#),

¹The importance of education depends on one reasonable assumption, namely that differences in real wages reflects differences in the value of human capital, either due to a difference in the stock of human capital or differences in the rental rate on human capital. Then, differences in the growth of real wages reflects differences in the return to human capital accumulation.

²See e.g. [Chetty et al. \(2011\)](#) for a discussion of the difference between estimates of the *i.e.s.* for the intensive and extensive margin.

Browning et al. (1985); Altonji (1986); Abowd and Card (1987); Ham and Reilly (2002); French (2005)).³ However, as first noted by Heckman (1976), the assumption of exogenous wages may bias the estimate of the *i.e.s.* downwards. Imai and Keane (2004) and Wallenius (2011) estimate life cycle models with human capital using micro data, and find estimates of the *i.e.s.* of 3.8 and 0.8-1.3, respectively.⁴ The parameters reported by Imai and Keane (2004) and Wallenius (2011) refer to the *i.e.s.* with respect to changes in the total return to labor, and not only wages which is the focus here.^{5,6} As a comparison, I find an estimate of the *i.e.s.* for the total return to labor (or soon-to-retire-workers) of 0.45. Both Imai and Keane and Wallenius target annual labor supply, which implicitly assumes that all non-employment spells are voluntary.⁷ The use of labor supply measure is thus important: using a similar methodology but targeting only the intensive margin of labor supply, I find an estimate of the *i.e.s.* for soon-to-retire-workers which is about half of what Wallenius obtains and 1/12th of what Imai and Keane finds. This estimate is however likely to be biased downwards, as some of the changes in the extensive margin are voluntary and related to wage changes. But, given the large share of involuntary unemployment it seems reasonable to assume that the upward bias on the *i.e.s.* of targeting annual hours is considerably larger than the downward bias of only targeting the intensive margin. Moreover, it serves as an important benchmark for the *i.e.s.* of the intensive margin in models with human capital accumulation.

Second, I find that there is a large heterogeneity across workers with respect to the return on human capital, and thus a large heterogeneity *w.r.t.* the intertemporal elasticity of substitution. Whereas workers soon-to-retire has an *i.e.s.* of 0.45, the estimate of the *i.e.s.* for workers aged 25 is only 0.22 and 0.29 for workers with and without a college degree, respectively. Thus, the estimate of the intertemporal elasticity of substitution of labor for college graduates aged 25 is less than half of the estimate for workers soon-to-retire. And, young workers without a college degree have 32 percent higher *i.e.s.* than young college educated. Using population weights calculated from the CPS, and a share of 1/3 college graduates, the average *i.e.s.* in the population is 0.35. Thus, the average elasticity is well below the estimate of the *i.e.s.* for workers soon-to-retire, which is identical to the estimate of the (inverse) curvature of the marginal disutility of labor. An estimate of the average *i.e.s.* of 0.35 is within the range of what is obtained in the micro literature, using a comparable

³See Pencavel (1986) for an early survey of this literature.

⁴See Keane (2011) for a survey of the effects of taxes on labor supply in both static models and dynamic models with human capital accumulation.

⁵Alternatively, it is the *i.e.s.* for the workers with zero return to human capital accumulation, which in their models is the workers soon-to-retire.

⁶When the *i.e.s.* is state-dependent, there is no longer a direct mapping from the utility parameter to the *i.e.s.* This is important to take into account when comparing estimates of the *i.e.s.* across different models. See also Keane and Rogerson (2012) for a discussion of the link between the utility parameter and the *i.e.s.*

⁷In order to minimize the effect of students, Imai and Keane (2004) use only observations for workers the year after they last reported to be students. However, as the student status is the current status whereas the labor supply is asked in retrospect "hours worked last calendar year", Imai and Keane still include a large share of students in their sample and will have an increase in their labor supply measure as students graduate and start working.

sample with respect to age and education composition.

The structural estimates of the intertemporal elasticity of substitution by different education groups are novel. However, previous studies has argued that the response of labor supply to temporary wage fluctuations would differ across age, see [Shaw \(1989\)](#), [Imai and Keane \(2004\)](#) and [Keane \(2012\)](#). Shaw estimates a life cycle model with human capital and argues that the elasticity is increasing with age. However, due to the choice of utility function she cannot recover the *i.e.s.*. Imai and Keane compute the uncompensated response of hours to a temporary shock to wages, and find that it increases sharply with age: at age 20 workers are found to have an implicit elasticity of 0.3, whereas at age 60 they find an implicit elasticity which is more than 5 times larger (1.7). However, as shown by [Wallenius \(2011\)](#) the model by Imai and Keane has poor out of sample fit for older workers. As explained below, this gives a substantial overestimation of the response by older workers. Moreover, neither of these studies consider educational differences.

The state-dependency of the *i.e.s.* indicates that one should be cautious when comparing estimates of the intertemporal elasticity of substitution obtained from different samples with respect to e.g. the age and education distribution. Moreover, it provides a theoretical explanation for why studies find that the labor supply elasticity increases with the wealth distribution (see e.g. [Ziliak and Kniesner \(1999\)](#)) and increases with age and decreases with education (see e.g. [Blau and Kahn \(2007\)](#)). Analyzing the life cycle labor supply effects of taxes, Ziliak and Kniesner find that the intertemporal elasticity of substitution increases by about 39 percent from the lowest wealth quartile to the top quartile.⁸ This is consistent with the findings in this paper, as wealth and the *i.e.s.* both increase over the life cycle. Looking at the wealth quartiles of the simulated data from the model, which is however not matched to real data, I find that the *i.e.s.* increases by 32 percent from the lowest to the top quartile. Blau and Kahn estimate labor supply elasticities for married women, and analyze the elasticity separately for different age groups and different education groups. They find that the intertemporal elasticity of substitution increases sharply with age, and falls with education, which is consistent with a model of human capital accumulation of the sort presented in this paper.⁹

[Keane \(2012\)](#) finds that welfare costs associated with permanent tax changes are large, once the effects of human capital are properly taken into account. Whereas human capital dampens the effect of transitory tax changes for young workers, because it does not affect the return to human capital, Keane shows that human capital amplifies the effect of permanent tax changes through a "snowball-effect". A decline in current labor supply reduces (expected) future wages through a lower production of human capital. Lower future wages reduces future

⁸Note that increase in the *i.e.s.* over wealth quartiles most likely is too large. I find that the negative bias of excluding human capital is largest for young workers, which typically also are wealth-poor workers. Thus, as the estimation bias shrinks with age, it most likely also shrinks with wealth quartiles. Thus, the increase in estimates of the *i.e.s.* over wealth quartiles is overstated.

⁹Note that the estimates of [Blau and Kahn \(2007\)](#) are however likely to be biased to zero, as they do not take into account that wages are not exogenous to the labor supply decision. And, in light of the findings in this paper, the estimation bias for younger workers and higher educated workers are larger.

labor supply, and thus further lowers future wages. Combined with a high intertemporal elasticity of substitution, Keane finds that this snowball-effect is large, and the welfare costs of permanent tax changes are large, and more than 4 to 7 times larger than what is found in conventional models excluding the effects of human capital. Performing a similar exercise as Keane, but using the model estimated below, I find that human capital do amplify the effect of permanent tax changes, but the amplification effect is small. In response to a 5 percentage point permanent tax increase, welfare, measured in consumption loss, is reduced by 1.99 percent and 2.12 percent for non-college workers and college workers, respectively. In a model without human capital, the corresponding consumption loss is 1.5 percent for both education groups. The amplification effect of human capital is much smaller due to both a much lower intertemporal elasticity of substitution, but also due to a better model fit. As shown by Wallenius (2011), the out-of-sample fit of the model by Imai and Keane, which is above age 36, is poor. Hours and wages fall to sharply towards zero. With decreasing returns to scale, the level of hours matters for the snowball effect: the lower is the labor supply, the larger is the production of human capital per unit of labor supply, and the larger is the corresponding reduction in the production of human capital due to a tax change.

The remainder of the paper is organized as follows. Section 2 presents the life cycle model. Section 3 describes the data used in the estimation, and section 4 explains the estimation strategy and present the results. In section 5, the estimation bias of the *i.e.s.* is discussed in more detail, and section 6 provides some robustness checks. Section 7 examines the welfare costs of tax changes in the model estimated in section 4, and finally, section 7 concludes.

1.2 Model

The model is a discrete-time life cycle model for a finitely lived agent facing human capital uncertainty. I use the deterministic model of Wallenius (2011), and add wage/human capital uncertainty in the same way as Imai and Keane (2004). The agent is endowed with one unit of time at each date, and retirement is exogenously imposed at a given age. For simplicity, I omit age subscripts on the variables since there is a one to one relationship between time, t , and age, a . The agents are subject to an idiosyncratic shock to the stock of human capital at the beginning of each period, and must have non-negative assets at death.

The agent has separable preferences over consumption, c , and hours worked, n , given by

$$\mathbb{E}_t \sum_{t=0}^T \beta^t [U(c_t) - v(n_t)], \quad (1.1)$$

where β is the discount factor and \mathbb{E}_t is the expectation operator, where the expectation is taken with respect to future human capital shocks. U is a concave function, v is a convex function, and they are both continuous and twice differentiable. A working age agent faces an intertemporal budget constraint

$$c_t + k_{t+1} \leq (1 + r)k_t + w_t n_t,$$

where k_t is the asset holdings at time t , r is the interest rate on assets, and w_t is the hourly wage at time t .¹⁰ The observed wage per hour at age t is defined as the product of the stochastic human capital stock $\varepsilon_t h_t$ and the rental rate on human capital p_t^h :

$$w_t = p_t^h \varepsilon_t h_t, \quad (1.2)$$

where the shock to the human capital stock, ε_t , is assumed to be a mean one, *i.i.d.* stochastic process with a log-normal distribution,

$$\ln(\varepsilon_t) \sim N\left(-\frac{1}{2}\sigma^2, \sigma^2\right).$$

The shock to the human capital stock may be thought of as a shock to the depreciation rate of human capital. Note that although the shock is *i.i.d.*, the effect on future wages is persistent through the human capital channel: a high shock today increases labor supply and human capital accumulation, and thus increases future wages.

The choice of introducing uncertainty into the model may have important effects on the estimate of the *i.e.s.*. If workers are risk averse, the human capital shock will decrease the expected utility weighted return of human capital, as low realizations of the shock gets a higher weight than high realizations. This will decrease the return to labor. However, if asset markets are incomplete, labor supply may act as an insurance device against idiosyncratic risk which increases the return to labor. First, in order to smooth consumption, workers may increase labor supply in response to a low human capital shock today.¹¹ Second, as workers accumulate human capital while working, labor supply also acts as an insurance device against low shocks to human capital in the future. As young workers are typically also poor workers who need insurance the most in order to smooth consumption, they have a stronger incentive to increase labor supply today in response to a bad shock and to insure against future wage shocks. This increases the expected utility weighted return of human capital. Moreover, if asset markets are incomplete, uncertainty about future wages will lead to precautionary savings for poor workers.¹² Thus, the return to labor will increase for these workers, as their marginal utility of consumption increases. As young workers are typically poor workers, they have a stronger precautionary savings effect. Thus, the effect due to incomplete markets increases the return to labor, and more so for young workers. The total effect is unclear: whether or not uncertainty makes the life cycle profile for the total return to labor, and thus optimal labor supply profile, steeper or flatter is determined by the parameters. A steeper (flatter) profile for the optimal labor supply results in a lower (higher) estimate of the *i.e.s.*, compared to the model without uncertainty.

Following [Imai and Keane \(2004\)](#) and [Wallenius \(2011\)](#) I assume that the rental rate on human capital is constant for all ages and normalizes it to one for all time periods. This implies that the wage rate equals the current stock of human capital, $w_t = \varepsilon_t h_t$.

¹⁰The price of consumption is normalized to 1.

¹¹[Pijoan-Mas \(2006\)](#) finds that households use work effort extensively as a mechanism to smooth consumption when facing uninsurable idiosyncratic productivity risk.

¹²See e.g. [Low \(2005\)](#) for a discussion of how precautionary motives affects labor supply over the life cycle.

I assume that human capital accumulation is limited to learning-by-doing, or equivalently, is a by-product of market work. The more time a worker spends in the market, the higher is the accumulation of human capital. Human capital evolves according to

$$h_{t+1} = (1 - \delta)\varepsilon_t h_t + G(n_t, \varepsilon_t h_t, a_t), \quad 0 \leq \delta \leq 1, \quad (1.3)$$

where δ is the rate of depreciation and $G(n_t, \varepsilon_t h_t, a_t)$ is the production function of human capital, which is concave, twice differentiable and increasing in n_t and $\varepsilon_t h_t$. Age is included in the function to allow for different human capital production at different ages.

Workers maximize life time utility with respect to consumption, labor supply, asset holdings and human capital accumulation. The value function is given by

$$V_t(k_t, h_t, \varepsilon_t) = \max_{c_t, k_{t+1}, n_t, h_{t+1}} \{u(c_t) - v(n_t) + \beta \mathbb{E}_t V_{t+1}(k_{t+1}, h_{t+1}, \varepsilon_{t+1})\},$$

and maximized subject to

$$c_t \leq \begin{cases} (1+r)k_t - k_{t+1} + \varepsilon_t h_t n_t, & t < \hat{T} \\ (1+r)k_t - k_{t+1} + \bar{P}, & \text{if } t \geq \hat{T} \end{cases}, \quad (1.4)$$

$$h_{t+1} = (1 - \delta)\varepsilon_t h_t + G(n_t, \varepsilon_t h_t, a_t), \quad t < \hat{T} \quad (1.5)$$

$$k_{T+1} = 0, \quad (1.6)$$

$$0 \leq n_t \leq 1, \quad \forall t < \hat{T}, \quad n_t = 0 \quad \forall t \geq \hat{T} \quad (1.7)$$

$$c_t \geq 0, \quad k_0, h_0 \text{ given} \quad (1.8)$$

where \bar{P} is the pension benefit, and \hat{T} is the exogenously imposed retirement age.

Let λ_t denote the Lagrange multiplier on the age t budget constraint, and μ_t the multiplier on the age t human capital accumulation constraint. The first order conditions are

$$c_t : u'(c_t) = \lambda_t, \quad \forall t \quad (1.9)$$

$$k_{t+1} : \lambda_t = \beta \mathbb{E}_t \frac{\partial V_{t+1}(k_{t+1}, h_{t+1}, \varepsilon_{t+1})}{\partial k_{t+1}}, \quad t < \hat{T} \quad (1.10)$$

$$n_t : v'(n_t) = \lambda_t \varepsilon_t h_t + \mu_t \frac{\partial G(n_t, \varepsilon_t h_t, a_t)}{\partial n_t}, \quad t < \hat{T}, \quad \varepsilon_t = 1 \quad (1.11)$$

$$h_{t+1} : \mu_t = \beta \mathbb{E}_t \frac{\partial V_{t+1}(k_{t+1}, h_{t+1}, \varepsilon_{t+1})}{\partial h_{t+1}}, \quad t < \hat{T} \quad (1.12)$$

Using the envelope conditions to substitute for the derivatives of the value function yields the following equations

$$u'(c_t) = \beta(1+r)\mathbb{E}_t u'(c_{t+1}), \quad (1.13)$$

$$v'(n_t) = u'(c_t)\varepsilon_t h_t + \mu_t \frac{\partial G(n_t, \varepsilon_t h_t, a_t)}{\partial n_t}, \quad (1.14)$$

$$\mu_t = \beta \mathbb{E}_t \left(\left((1 - \delta)\varepsilon_{t+1} + \frac{\partial G(n_{t+1}, \varepsilon_{t+1} h_{t+1}, a_{t+1})}{\partial h_{t+1}} \right) \mu_{t+1} + \varepsilon_{t+1} u'(c_{t+1}) n_{t+1} \right) \quad (1.15)$$

Equation (1.13) is the familiar consumption Euler equation. Equation (1.14) equates the marginal disutility of labor to its marginal benefit. The first term on the *r.h.s.* is the effect on current utility from higher labor income. The second term is the learning effect; working an additional hour increases human capital and hence future wages. Multiplying the learning effect with the shadow price on skill, μ , gives the marginal utility of increased human capital. Equation (1.15) is the law of motion for the shadow price of skill.

Equation (1.14) demonstrate why the *i.e.s.* is no longer a constant, but a state-dependent variable: Due to human capital accumulation, the return to labor is a function of both the contemporaneous wage and discounted future gains in wages. As transitory wage shocks only affects the contemporaneous term, workers with a high future gains in wages (in relative terms) will respond less to transitory shocks compared to workers with low gains in future wages.¹³

Let's define the *i.e.s.* as the percentage change in hours over time in response to an exogenous unanticipated temporary change in the rental rate on human capital. And, assume that the disutility of labor and the production function of human capital takes the following functional forms

$$\begin{aligned} v(n_t) &= b \frac{n_t^{\frac{1}{\gamma}+1}}{\frac{1}{\gamma}+1}, \quad b \geq 0, \gamma > 0, \\ G(n_t, \varepsilon_t h_t, a_t) &= A \exp(-da_t) \varepsilon_t h_t n_t^\alpha, \quad 0 \leq \alpha \leq 1, A, d \geq 0. \end{aligned}$$

Then, the *i.e.s.* is defined as¹⁴

$$\frac{d\left(\frac{n_t}{n_{t+1}}\right)}{dp_t^h} \frac{p_t^h}{\frac{n_t}{n_{t+1}}} = \gamma \frac{1}{\left(b n_t^{\frac{1}{\gamma}-1} - \gamma \mu_t \frac{\partial^2 G_t}{\partial n_t^2}\right)} \left(u'(c_t) \varepsilon_t h_t + \frac{\partial G_t}{\partial n_t} \frac{\partial \mu_t}{\partial p_t^h} \right) \frac{p_t^h}{n_t} \left(1 - \frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{\partial G_t}{\partial n_t} \frac{n_t}{n_{t+1}} \right). \quad (1.16)$$

Without human capital accumulation $\frac{\partial G_t}{\partial n_t}$ is zero, and the *i.e.s.* is equal to γ . With human capital the *i.e.s.* possibly depends on all state variables; human capital, asset position, the shock to the human capital stock and age, and all parameters of the model.

Let's analyze how the *i.e.s.* will evolve over the life cycle. For all parameter values considered below, the product $\frac{\partial G_t}{\partial n_t} \frac{\partial \mu_t}{\partial p_t^h}$ is very close to zero, and so is $\frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{\partial G_t}{\partial n_t} \frac{n_t}{n_{t+1}}$. This implies that the importance of the state-dependency of the *i.e.s.* does not come from that fact that it alters also future labor supply decisions through the human capital effect. Instead, the importance of human capital in making the *i.e.s.* state-dependent is to change the "pass-through" of wage changes. As wages is only a fraction of the return to labor, and this fraction changes with age, so does the labor supply elasticity. In order to simplify the expression, I therefore impose that $\frac{\partial G_t}{\partial n_t} \frac{\partial \mu_t}{\partial p_t^h} = \frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{\partial G_t}{\partial n_t} \frac{n_t}{n_{t+1}} = 0$, such that the expression becomes

¹³See also Keane (2012) and Keane and Rogerson (2012) for a similar discussion of the effects of human capital.

¹⁴For a more detailed calculation of the *i.e.s.*, see the appendix.

$$\frac{d\left(\frac{n_t}{n_{t+1}}\right) \frac{p_t^h}{n_{t+1}}}{dp_t^h} = \gamma \frac{1}{\left(1 + \frac{1}{u'(c_t)p_t^h \varepsilon_t h_t} \mu_t \frac{\partial G_t}{\partial n_t} (1 - \gamma(\alpha - 1))\right)}. \quad (1.17)$$

As shown below, the shadow price on skills, μ_t , is decreasing over the life cycle as the working life horizon shrinks, contributing to an increase in the intertemporal substitutability of labor over the life cycle. The same is true for the slope of the production function of human capital, $\frac{\partial G_t}{\partial n_t}$, both due to decreasing returns to scale in the production of human capital and because learning becomes more difficult with age ($d > 0$). Moreover, due to consumption smoothing, the increase in wages is larger than the increase in consumption over the life cycle, so that $\frac{1}{u'(c_t)\varepsilon_t h_t p_t^h}$ is decreasing over the life cycle. Again, this contribute to an increasing *i.e.s.* over the life cycle. Hence, the *i.e.s.* will be increasing over the life cycle, as contemporaneous wages becomes relatively more important for the workers, and will approach γ , which is the *i.e.s.* of the workers in the last period before retirement (when $\mu_{\hat{T}} = 0$).

The larger is the fall in the shadow price on skills over the life cycle, the larger is the increase in the *i.e.s.* over the life cycle, and the further apart is the average intertemporal elasticity of substitution of labor from the value of γ . As more education is associated with a higher return to human capital for young workers, and thus larger fall in the shadow price on skills over the life cycle, the *i.e.s.* should increase more for higher educated workers. The state-dependency of the *i.e.s.* is further explored below, in section 4.

Note that the response of labor supply to a human capital shock, ε_t , would be different than the response to changes in the rental rate, as ε_t changes the whole future path of expected wages and then also the expected return on current human capital accumulation.

1.3 Data

The choice of using data from the CPS is motivated by the findings in [Wallenius \(2011\)](#); she shows that the life cycle profile implied by the estimates found in [Imai and Keane \(2004\)](#), using a life cycle profile based on individuals aged 20-36 years, have poor out of sample fit and stress the importance of using long life cycle profiles, which is possible using the CPS. I use monthly CPS data from 1979 to 2008, and construct an average life cycle profile for wages and labor supply for individuals aged 25 to 60 years, using 17 consecutive cohorts.¹⁵ As shown below, there are large differences in hours and wages across education levels. The main educational difference is between those with and those without a college degree. I therefore choose to split my sample in workers with a college degree and workers without a college degree. To make my results comparable with most of the literature, I limit my sample to white males.¹⁶ I use only data on individuals which are in the labor force and have well defined hours and wage data.¹⁷

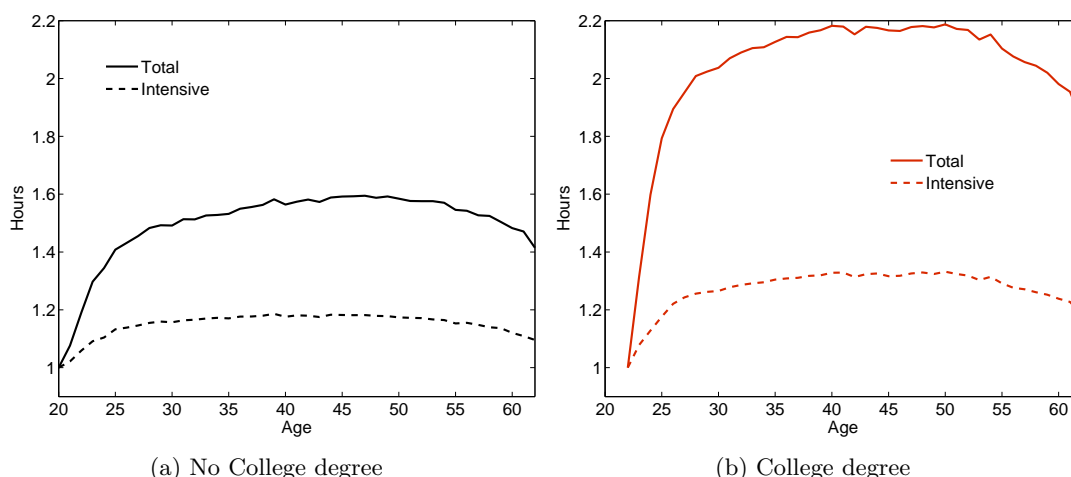
¹⁵The data are from CEPR, Center for Economic and Policy Research. 2006. CPS ORG Uniform Extracts, Version 1.5 . Washington, DC

¹⁶I also exclude individuals that are students, have served in the military and self employed workers.

¹⁷I include only individuals with usual weekly hours above 4 hours and below 99 hours.

Unlike both Imai and Keane (2004) and Wallenius (2011), I start my sample at age 25 instead of at age 20, and I use monthly data on "usual weekly hours" instead of annual data on "usual weekly hours" multiplied by "weeks worked". This is motivated from the desire to find the best measure of labor supply, when estimating the *i.e.s.*. The life cycle profile for "usual weekly hours", labeled "intensive", and "usual weekly hours x weeks worked", labeled "total", are plotted in figure 1.1 for workers with and without a college degree.¹⁸ Given that wages exhibits its largest increase in the period between age 20 and age 30, the choice of labor supply measure matters for the estimate of the *i.e.s.*: the larger is the increase in the optimal labor supply, the stronger is the relation between wages and hours, and the higher is the estimate of the intertemporal elasticity of substitution. The natural question to ask is then: what is behind this sharp increase in the extensive margin, i.e. "weeks worked", plotted in figure 1.2.

Figure 1.1: Life cycle patterns for different measures of hours, age averages.



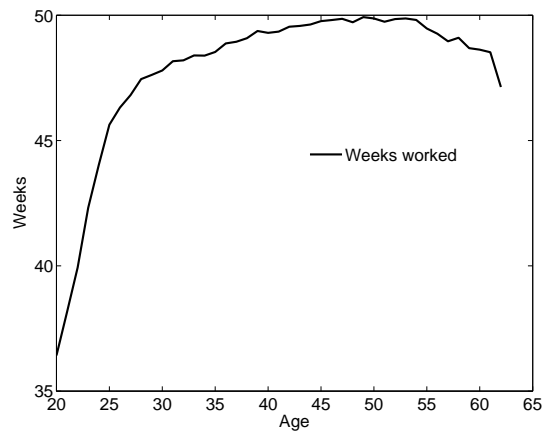
Note: March CPS data from 1979 to 2008. Age averages of 14 consecutive cohorts. The profiles are normalized to 1 at age 20 for workers with no college degree, and at age 22 for workers with a College degree. The two measures are calculated as follows: Total= "usual weekly hours"* "weeks worked last year", and Intensive="usual weekly hours",

The large increase in the no. of weeks worked is due to a decline in the average number of weeks workers are unemployed, see figure 1.3(a), and a sharp increase in the participation rate, *i.e.* a sharp decline in the no of weeks out of the labor force, see figure 1.3(b).

Let's first analyze the nature of unemployment. Using monthly CPS data on labor market transitions from 2001 to 2007, which span one business cycle defined by the NBER, I compute the share of voluntary and involuntary employment to unemployment transitions and the

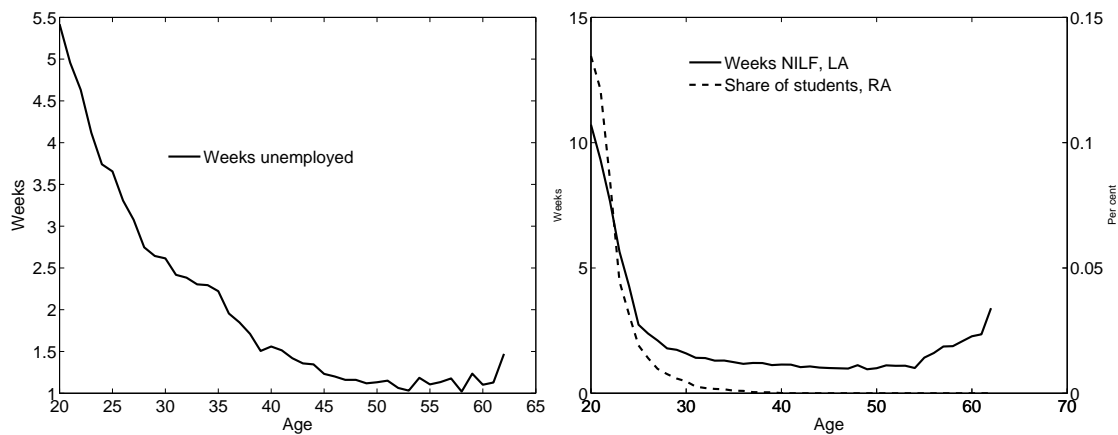
¹⁸Data from: Miriam King, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick. Integrated Public Use Microdata Series, Current Population Survey: Version 3.0., Minneapolis: University of Minnesota, 2010.

Figure 1.2: Weeks worked, age averages.



Note: March CPS data from 1979 to 2008. Age averages of 14 consecutive cohorts.

Figure 1.3: Weeks unemployed, weeks not in the labor force, and the share of students. Age averages.



Note: March CPS data from 1979 to 2008. Age averages of 14 consecutive cohorts.

job finding probability of workers with and without a college degree.^{19,20,21} The fraction of voluntary unemployed are slightly higher for the workers with a college degree, but the fraction are small for all ages, see figure 1.4.²² Given that I cannot distinguish between voluntary and involuntary unemployment in data used in the estimation below, I argue that changes in the extensive margin due to unemployment should not be included in the measure of optimal

¹⁹Voluntary unemployed is defined as those who report that they are unemployed because they "quit job". The involuntary are those who are unemployed due to "temporary job ended", "lost job" or "on layoff".

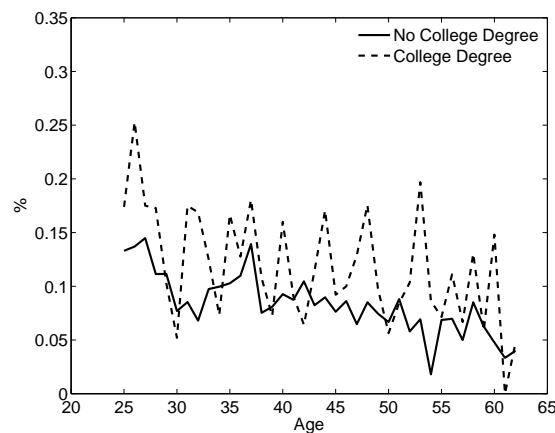
²⁰The data are collected from the NBER. I match individual transitions based on household identifiers, age, sex, race, individual line number and months in sample. Due to limitations on available data I cannot calculate these measures for the whole time period from 1979 and onwards.

²¹I use data that spans one business cycle due to Shimer (2007) findings that there are substantial fluctuations in the job finding probability at business cycle frequencies.

²²I also find that there is no significant difference between the job finding probability of the two groups. Results are available on request.

labor supply.

Figure 1.4: Job separation probability, share of voluntary quits. Age averages.



Note: Monthly CPS data from 2001 to 2007.

Second, the sharp decrease in weeks out of the labor force goes hand in hand with a sharp decrease in the share of students in the sample, see 1.3 (b). This indicates that a part of the increase in the extensive margin is due to sample selection issues: students aged 20-25 work on average 21 weeks opposed to the average of non-students of 43 weeks, thus as the share of students decline the average weeks worked in the sample increases significantly. The choice of years of education, and thus the choice of low labor supply during studies, is linked to the expected wage increase over the life cycle, not just the expected wage in the years shortly after leaving university. Thus, the choice to increase labor supply the year after leaving university is not directly linked to the wage increase experienced in the same period, and should not be used in the estimation of the *i.e.s.* Due to the nature of the annual data I cannot remove students from the sample.²³ In order to minimize the sample selection issue due to students entering the labor force, I therefore start the sample at age 25, when most individuals have finished their studies.

Excluding the weeks workers are unemployed from the measure of labor supply, due to the finding that most unemployment is involuntary, reduces the measure of labor supply towards the measure of the intensive margin, see figure 1.5.²⁴ For non-college-graduates the two measures are almost identical, and for college graduates the measure of total labor supply excluding unemployment lies inbetween the two other measures. However, once starting at age 25, the three measures of labor supply are very similar. Looking at the increase in wage dispersion over time, Lemieux (2006) finds that "... The main problem with the March CPS is that it poorly measures the wages of workers paid by the hour (the majority of the work force)", and suggests using monthly data on ORG CPS instead. To be robust

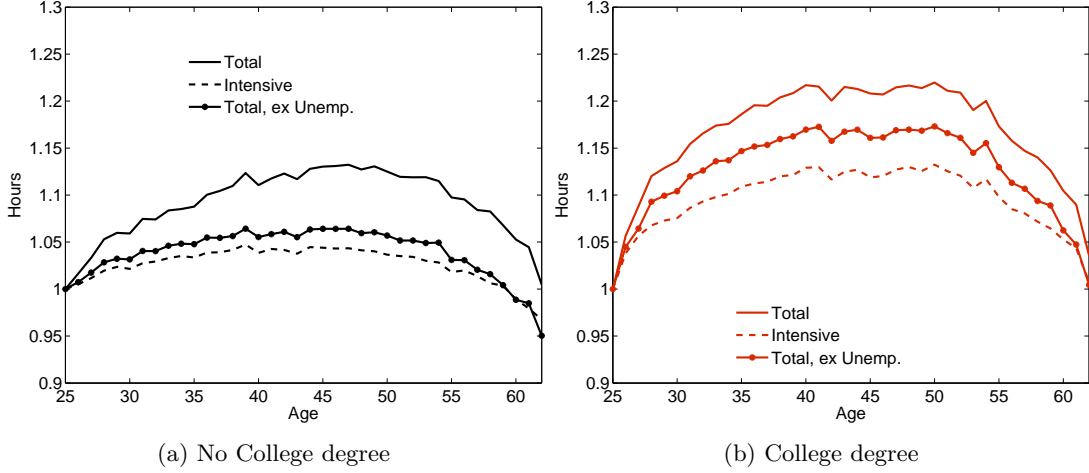
²³In the CPS (and in the NLSY), the student status refers to the time of the interview, whereas data on labor supply refer to the year preceding the interview. Thus, I cannot detect students that left university during the last year, and possibly had low labor supply during that year.

²⁴The measure of total labor supply, exclusive changes in unemployment is calculated as follows

$$Total, exUnemp = \frac{weeks\ worked * usual\ weekly\ hours}{(52 - weeks\ unemployed) * 14 * 7}$$

towards measurement errors in the wage data I therefore use monthly data, and thus restrict the labor supply measure to only include the intensive margin. Thus, the intertemporal elasticity of substitution estimated refers only to the intensive margin. However, given that most unemployment spells are involuntary and given that the measure of total labor supply excluding unemployment is so similar to the intensive margin, I do believe that *i.e.s.* of the total labor supply is similar to the elasticity obtained here.

Figure 1.5: Life cycle patterns for different measures of hours, age averages.



Note: March CPS data from 1979 to 2008. Age averages of 14 consecutive cohorts. The profiles are normalized to 1 at age 25. The three measures are calculated as follows: Total= "usual weekly hours"* "weeks worked last year", Intensive="usual weekly hours", and 'Total, ex Unemp.' =(("usual weeks worked"*"usual weekly hours")/((52-"weeks unemployed")*14*7))

In the model, the period time endowment is assumed to be equal to one. As is standard in the literature, I assume that the maximum time allotted to work is 14 hours a day 7 days a week. The fraction of hours worked by an employed individual in a given period is hence

$$hours = \frac{'usual weekly hours'}{14 * 7}.$$

The hourly wage is computed as

$$wage = \frac{'usual weekly earnings'}{'usual weekly hours'},$$

and is deflated by the CPI to make it comparable across time.

The life cycle profiles for hours and wages are constructed from an average cohort. Unfortunately, the monthly data starts in 1979, and I thus do not have enough years to cover a full life cycle, from 25 to 62 years, for one cohort. I therefore take the average of several cohorts. In order to have a minimum of 5 observations at each age, I use 17 consecutive cohorts starting with those who were 21 years old in 1979, and continuing with the those who were 24 in 1979, and so forth up to those who were 37 in 1979. I take the average growth rate by age of the three variables, and combine these with the initial condition given by the

average outcome of individuals aged 25 years. The profile obtained for hours and wages are very robust to changes in number of cohorts once I end my sample at age 60. I therefore limit my sample to individuals aged 25 to 60 years old.

In addition to the age effect, there is a significant time effect in the data.²⁵ Given that I merge different cohorts, and that the focus of this paper is on the age effect (life cycle effect), I want to remove the time effect from the data. I adjust the growth rates of all variables for all cohorts for the education specific average growth in the sample

$$\Delta \tilde{x}_{a,i,t} = \Delta x_{a,i,t} - \Delta \bar{x}_{i,t}, \quad \forall t = 1980 : 2008, \quad a = 21 : 62, \quad i = 1, 2,$$

where $\Delta x_{a,i,t}$ is the change in e.g. the average wage for individuals with age a , education level i , at time t , and $\Delta \bar{x}_{i,t}$ is the change in the age average of wages for individuals with education level i at time t .²⁶ Assuming that the rental rate on human capital evolves according to the education specific average growth rate of wages, the growth adjustment of wages can be seen as removing the changes in the rental rate on human capital over time, and hence making the data more comparable with the model.

Due to a limited sample size and possibly sampling errors, the life cycle profiles are jagged. Since I do not want the estimates to be influenced by these issues, I choose to smooth the data.²⁷ The life cycle profiles of wages and hours for smoothed and unsmoothed data and the variance of wages of unsmoothed data are plotted in figure 1.6. Both wages and hours are hump-shaped over the life cycle for both education groups.

The variance of wages are similar for both education groups at age 25, but the variance increases much less over the life cycle for non-college graduates. This is consistent with the modeling choice of a complementarity between labor and human capital in the production of human capital, which increases the variance of human capital in the level of human capital.

1.4 Estimation

The model is estimated using simulated method of moments, where I minimize the sum of squared percentage deviation of averages of hours and wages by age for both education groups.^{28,29} The model period is set to one year.

In order to solve the model, I must specify functional forms, initial level of human capital and assets and the exogenous age of retirement and death. All individuals enter the labor

²⁵There is potentially cohort effects present in the data, as I merge several cohort. However, analysing life cycle profiles of inequality in wages and hours [Heathcote et al. \(2005\)](#) find no evidence that cohort effects are important. I therefore abstract from cohort effects.

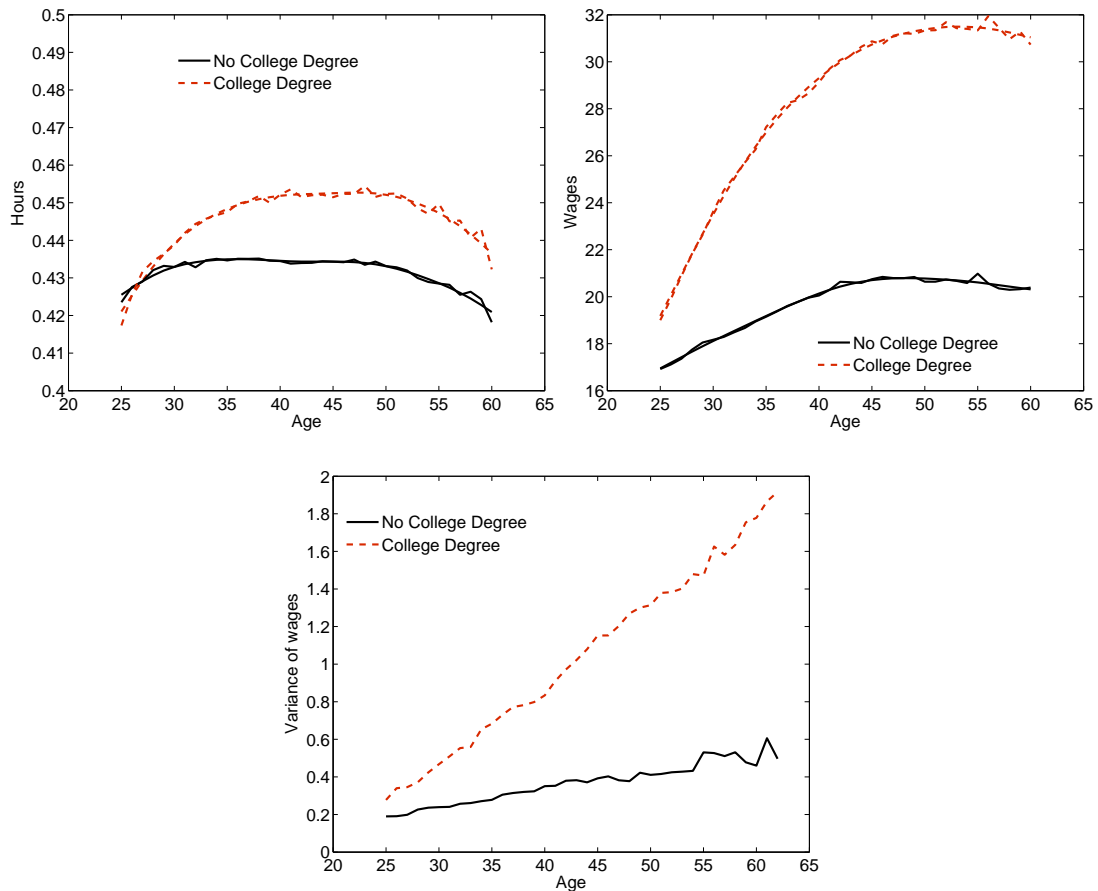
²⁶I control for changes in age distributions over time, by using the same age-weighting each year.

²⁷In particular I smooth the data using a Hodrick-Prescott filter with a smoothing parameter of 75 for real wages and the unemployment rate and 30 for hours.

²⁸The simulated moments are constructed in the following way: I solve the model for a particular parameter guess, simulate the life cycle profile for 50000 individuals, and then compute average hours and wage profiles at a given age. I then compute the age averages of the two variables.

²⁹In the weighting matrix I put double weight on the moments of labor supply, in order to obtain a good match for both variables.

Figure 1.6: Wages, hours and the variance of wages. Age averages.



Note: Monthly CPS data from 1979 to 2008. Age averages of 14 consecutive cohorts. The two lines per education groups show the raw data and the smoothed data.

force at age 25, retire at age 62, and after 15 years in retirement they exogenously die at age 77.³⁰ I further assume that the initial level of assets is set to zero, $k_{25} = 0$, and that the initial level of human capital is set to match the educational difference between the two education groups at age 25. In particular, the initial level of human capital is set to one for workers without a college degree and to 1.13 for workers with a college degree. Both education groups are assumed to have the same preferences, but differs in the production function of human capital. I use the following functional forms for preferences and the human capital production function, $G(\cdot)$

³⁰The age of death in the model is motivated by the life expectancy at age 20 for white males in the US, which is 76.8 years (Source: U.S. National Center for Health Statistics, National Vital Statistics Reports (NVSr), Deaths: Preliminary Data for 2008, Vol. 59, No. 2, December 2010.)

$$u(c_t) = \ln(c_t), \quad (1.18)$$

$$v(n_t) = b \frac{n_t^{\frac{1}{\gamma}+1}}{\frac{1}{\gamma}+1}, \quad b \geq 0, \gamma > 0, \quad (1.19)$$

$$G^i(n_t, \varepsilon_t h_t, a_t) = A^i \exp(-d^i a_t) \varepsilon_t h_t n_t^{\alpha^i}, \quad 0 \leq \alpha \leq 1, A, d \geq 0, i \in \{NDC, CD\} \quad (1.20)$$

The functions for preferences and the production function for human capital are taken from Wallenius (2011). Preferences are assumed to be separable and consistent with a balanced growth path. The choice of utility function may have implications for the estimation result. In particular, since the intertemporal elasticity of substitution of consumption and labor are linked, the choice of log utility in consumption may affect the estimate of the inter-temporal elasticity of substitution of labor. The possibility of a higher risk aversion is explored in section 5.

The disutility function of labor supply is standard. Note that whereas γ is the intertemporal elasticity of substitution of labor with respect to temporary wage changes in a model without human capital, this is no longer true here. Here, γ refers to the intertemporal elasticity of substitution of labor with respect to the total return to labor supply³¹, or alternatively, γ refers to the intertemporal elasticity of substitution of labor with respect to wages for those workers who have no future gain of human capital accumulation, *i.e.* those workers who will retire next period.

The production function of human capital is a Cobb-Douglas with labor and human capital as inputs, where $A \exp(-da_t)$ is the productivity parameter. The choice of complementarity between labor and human capital in the production of human capital is due to the finding by *e.g.* Imai and Keane (2004) that the marginal effect of an hour on future wages is increasing significantly with current wages. If d is positive, human capital accumulation will be more demanding with age.³²

The pension benefit is set to 40% of the average income for an average individual over the life cycle.³³ In the model, only the product $\beta(1+r)$ matters for the labor supply. Hence, I cannot identify both, and I therefor set $r = 0.04$. In order to limit the number of parameters to estimate, I follow Wallenius (2011) and assume that the annual rate of depreciation, δ , is 3 per cent. This is in line with micro evidence on the wage costs of labor market intermittency provided by Kim and Polachek (1994), which find that the annual rate of depreciation is between 2 – 5 percent when controlling for unobserved heterogeneity and endogeneity issues. In the benchmark estimation I assume that the preference parameters, β , b and γ , are the same across education groups. However, in section 5 I show that the results are robust to assuming education specific preferences. For all estimations considered I assume education specific parameters for the human capital production function: d , A , and α .³⁴

³¹Or the opportunity cost of time (OCT), as *e.g.* Imai and Keane (2004) labels it.

³²This is a simpler production function than the one studied by Imai and Keane (2004). However, Wallenius (2009) shows that the results in Imai and Keane also applies to this production function.

³³According to French and Jones (2012), Social security replaces about 40% of pre-retirement earnings.

³⁴In a similar setup Wallenius (2011) cannot identify α . In the estimations below α seems to be well identified.

In addition I need to specify the distribution of the shock to human capital. First, I follow Wallenius (2011) and assume that there is no uncertainty. Second, I estimate the model using the distribution of the human capital shock estimated by Imai and Keane (2004). Using the variance of wages for the two education groups, which is not a target in the estimation, I evaluate the performance of the model with uncertainty. Moreover, by comparing the results obtained below I can assess the effect of uncertainty on the estimate of the *i.e.s.*, and by comparing my results to the ones obtained by Wallenius and Imai and Keane, I can assess the difference in results stemming from a different target for labor supply.

1.4.1 Results, no shock

Adjusting the labor supply profile to take into account that most of the changes in the extensive margin are involuntary or unrelated to the changes in wages gives an estimate of γ equal to 0.44, which is significantly lower than the estimates obtained by Wallenius (2011) (0.8 – 1.3) using the same model, see table 1.1. By using total annual hours as a measure for optimal labor supply, Wallenius seems to overestimate the intertemporal substitutability of labor supply.

Table 1.1: Parameter estimates deterministic model, targeting age 25-60.

		NCD		CD
γ	0.4358	A	0.1155	0.2588
b	21.2187	d	0.0194	0.0347
β	0.9558	α	0.4821	0.4706
SSE	0.0093			

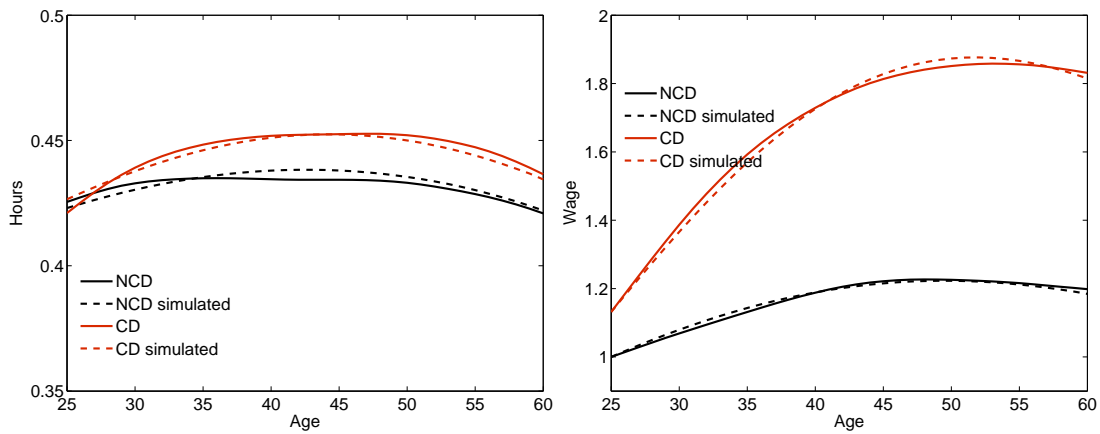
Note: Targets based on monthly CPS data from 1979 to 2008. 'NCD' refers to workers without a College degree and 'CD' refers to workers with a College degree. SSE is the sum of squared errors.

The model fit for hours and wages for the set of parameters estimated for the two education groups are plotted in figure 1.7. Apart from predicting to high labor supply among young college graduates, the model fits the targets well.

As shown above, the *i.e.s.* is state-dependent. Using equation 1.16, one can calculate the average *i.e.s.* by age and education, using the simulated data. Figure 1.8 plots the average *i.e.s.* by age and education. Although the *i.e.s.* for workers close to retirement is equal to the estimate of γ , the *i.e.s.* for young college graduates is as low as 0.2, *i.e.* less than half the value of γ . For workers without a college degree, the estimate of the *i.e.s.* for workers aged

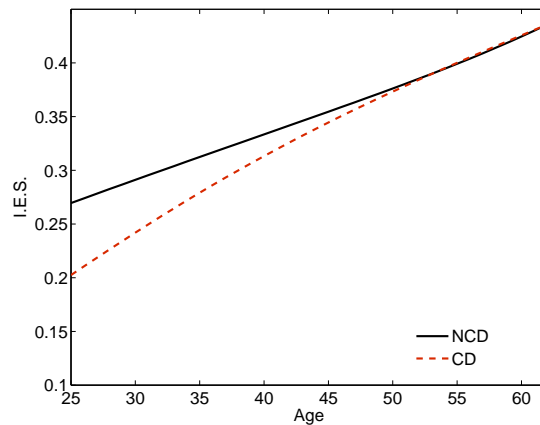
By performing the same estimations when fixing α at different values the model fit is varying. Moreover, I have also tried restricting d to be a common parameter, which gives about the same results as presented below, however with worse model fit. Apparently, I am able to identify α because I have two education groups with common preferences. As α is important for the choice of labor supply it is identified both from the curvature of real wages and curvature of the labor supply. The results of the estimations are presented in appendix B.

Figure 1.7: Model fit for hours and wages, targeting age 25-60.



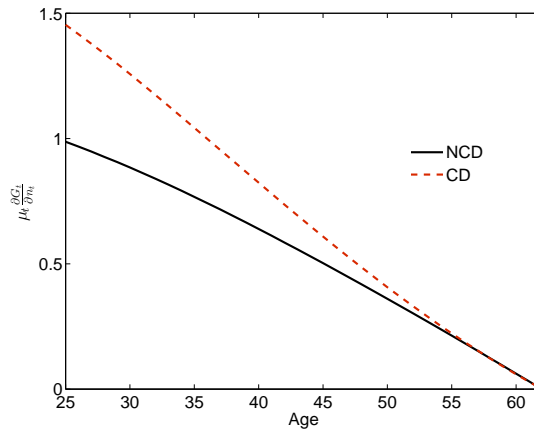
25 is 0.27 and it increases by 62 percent over the life cycle.³⁵ This implies that the average intertemporal substitutability in the population is much lower than the estimate of γ obtained above. Using a 1/3 share of college graduates, and the population weights from CPS, the average *i.e.s.* in the sample is 0.33, which is 25 percent lower than γ .

Figure 1.8: Intertemporal elasticity of substitution over the life cycle. Age averages of simulated data.



The difference in the intertemporal elasticity of substitution comes mainly from large differences in the return on human capital, see figure 1.9. Non-college graduates have 33 percent higher *i.e.s.* than college graduates, and 32 percent lower return on human capital than college graduates at age 25. As one approaches retirement, the gap between the return on human capital narrows, as does the gap between the intertemporal elasticities of substitution.

³⁵For more details on the calculation, see appendix A.

Figure 1.9: Returns to human capital, $\mu_t \frac{\partial G_t}{\partial n_t}$, for non-college graduates and college graduates.

1.4.2 Results, human capital shock

As shown above, the variance of human capital increases significantly over the life cycle, supporting the model choice of a stochastic human capital stock. Moreover, introducing uncertainty may influence the estimate of the *i.e.s.* due to the insurance role human capital then plays. As explained above, depending on the parameters, adding uncertainty may either increase or decrease the estimate of the *i.e.s.* compared to the model without uncertainty.

I use the distribution for the same shock estimated in [Imai and Keane \(2004\)](#), using NLSY-data for the cohort aged 20 in 1979:

$$\ln(\varepsilon_t) \sim N\left(-\frac{1}{2}0.05781^2, 0.05781^2\right), t > 25$$

Further, I set the standard deviation of the initial shock, ε_{25} , so that I match the education specific distribution of wages in the data. The estimate of γ increases slightly from 0.44 to 0.45 when uncertainty is introduced into the model, see table 1.2. This is however considerably lower than [Imai and Keane \(2004\)](#)'s estimate of 3.8, obtained using a similar model.³⁶ Consistent with the finding by [Wallenius \(2011\)](#), which shows that the high estimate obtained by Imai and Keane is due to the choice of sample (age 20 to age 36), I find a much lower estimate than Imai and Keane. Taking into account that wage uncertainty increases the estimate of the *i.e.s.* slightly, the labor supply measure induces a substantially lower estimate also compared to Wallenius.

The model fit for hours and wages are still good, see figure 1.10. Even though I do not estimate the distribution of the human capital shock, and I do not target the variance of the wages in the estimation, the model does surprisingly well in explaining most of the variance for wages for both education groups. However, at older ages the variance levels off in the model whereas it continues to grow for college educated in the data. The variance levels off as the variance of the production of human capital decreases. With d positive, production of

³⁶The difference in model between the one above and [Imai and Keane \(2004\)](#) should not influence the estimate of the *i.e.s.* significantly; using the same deterministic model as above, [Wallenius \(2011\)](#) obtains similar estimate to [Imai and Keane \(2004\)](#) when using the same age group.

Table 1.2: Parameter estimates stochastic model, targeting age 25-60.

			NCD	CD
γ	0.4514	A	0.1094	0.2525
b	19.3419	d	0.0184	0.0344
β	0.9529	α	0.4593	0.4487
SSE	0.0101			

Note: Targets based on monthly CPS data from 1979 to 2008. 'NCD' refers to workers without a College degree and 'CD' refers to workers with a College degree. SSE is the sum of squared errors. The simulated targets are based on a draw of 10000 individuals.

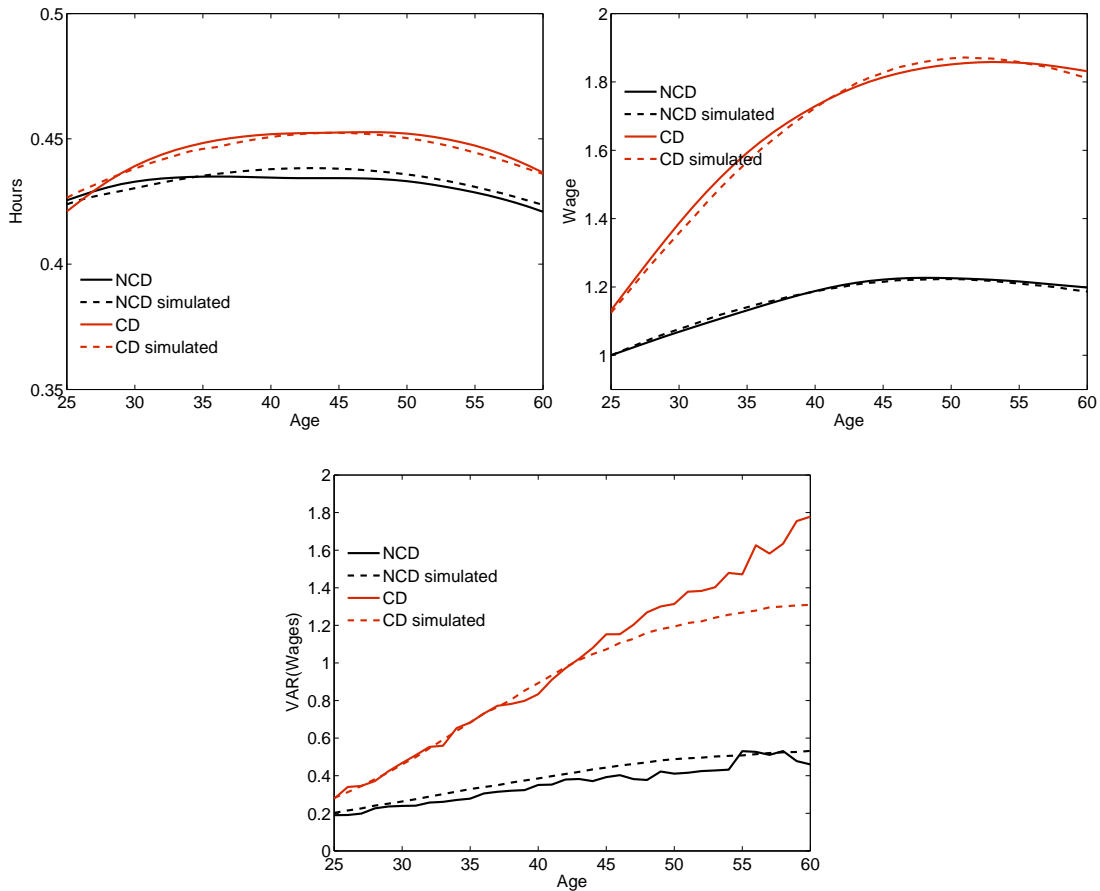
human capital is more difficult with age, irrespective of human capital level and labor supply. As a result, production of new human capital is very low for all older workers which together with a positive rate of depreciation of human capital slow down the increase in the wage dispersion.

Due to human capital, even a small wage shock can create a large increase in the variance of wages, and due to different production function of human capital across age groups the same shock gives rise to very different profiles for the variance of wages for the two groups.

As emphasized above, the *i.e.s.* is a state-dependent variable which can be computed using equation 1.16. The *i.e.s.* varies considerably across age and education groups; for non-college graduates the *i.e.s.* increases by about 58 percent whereas it more than doubles college graduates, see figure 1.11. Interestingly, the only state variables that seems to matter is age and education: the confidence interval around the conditional mean *i.e.s.*, which is computed using +/- two standard deviations of the conditional distribution, is narrow for both education groups. Using population weights from the CPS and a 1/3 share of graduate students, the average *i.e.s.* in the population is 0.35. This is 22 percent lower than the estimate of γ . Again, interpreting the estimate of γ as an estimate of the *i.e.s.*, overstates the average substitutability of labor with respect to transitory wage changes in the population. The results indicate that it is important to be cautious when comparing estimates of the *i.e.s.* obtained from different samples with respect to age and education, as there is no reason to expect that they should find the same estimate of the intertemporal elasticity of substitution.

Shaw (1989) was the first to note that the *i.e.s.* is increasing with age due to human capital accumulation, but she does not consider other state variables, and she cannot provide quantitative estimates for different ages due to her choice of preferences. Thus, I cannot compare my findings with her's. Using a similar model Imai and Keane (2004) find that the average (uncompensated) response in hours to a 2 percent unexpected wage increase grows exponentially with age; whereas hours increase by 0.6 percent for workers in their early twenties, hours increases by nearly 4 percent at age 60 and about 5.5 percent at age 65. Compared to Imai and Keane, I find both a much smaller response of hours at all ages,

Figure 1.10: Model fit for hours, wages and the variance of wages with stochastic human capital, targeting age 25-60.

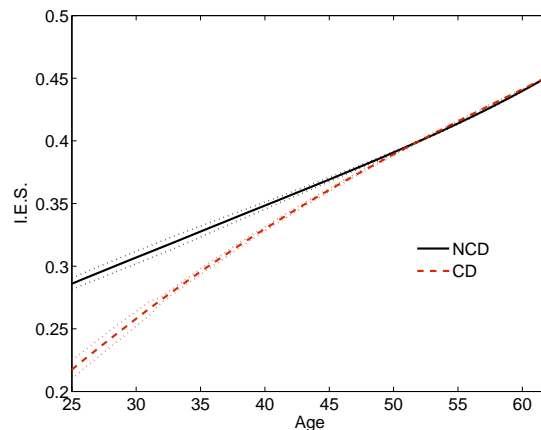


and a much smaller increase in the *i.e.s.* over the life cycle. However, Imai and Keane do not control for the income effect, which also is age-dependent, which makes comparisons a bit more difficult. The income effect is particularly important in models with human capital as temporary wage changes have persistent effects on future wages. With a higher estimate of the *i.e.s.*, labor supply responds more to wage changes which increases the persistence of the shock. Moreover, Imai and Keane do not distinguish between education groups, although they estimate different production functions for different educational groups.

Domeij and Floden (2006) argue that ignoring liquidity constraints will bias the estimate of the *i.e.s.* downwards. Once they exclude individuals likely to be liquidity constraint in their sample, their estimate of the *i.e.s.* more than doubles.³⁷ Human capital accumulation is an alternative source of an estimation bias, but has also some implications for the bias found when ignoring liquidity constraints. If liquidity constraint individuals are mainly young workers, which I find has the lowest *i.e.s.* in the population, when excluding these workers

³⁷However, the comparison is slightly wrong, as emphasised by Keane and Rogerson (2012), as credit constraints as human capital breaks the direct mapping between the preference parameter and the labor supply elasticity.

Figure 1.11: Intertemporal elasticity of substitution over the life cycle with stochastic human capital.



Note: Age averages of simulated data. The dotted lines are ± 2 standard deviation confidence intervals for the i.e.s. calculated from the simulated data.

the average *i.e.s.* in the population will increase due to the sample selection effect, and not only due to the importance of the liquidity constraint.

The state-dependency of the *i.e.s.* introduces some interesting policy implications with respect to e.g. labor taxation; young workers and in particular young college graduates will respond much less to contemporaneous tax changes than older workers. This implies that economies with a high share old workers will have a more tax-sensitive workforce relative to economies with a younger workforce. Also the distribution of education and or occupation may matter; the ability to accumulate human capital through learning by doing, and the value of human capital may differ significantly across education groups and occupations. Thus, economies with workers with high gains from human capital accumulation, here college graduates, will be less tax-sensitive, than economies with workers which have low gains from human capital accumulation.

1.5 Robustness

Above, I assumed that both education groups had common preferences. This is however possibly a strict assumption, as the two education groups differs significantly with respect to wage growth and wage dispersion, they may also differ significantly with respect to disutility of working. I therefore estimate the stochastic model without the assumption of common preferences. However, as the identification of α is related to the assumption of common preferences I assume that d is a common parameter as it is, together with α , and important parameter for the curvature of the wage profile. The results are shown in table 1.3.³⁸ Interestingly, when d is common, the estimates for γ are very similar across education groups, but are somewhat higher compared to the case with common preferences. As the estimates of γ are so similar across education groups, it is natural to ask why the estimate differs from the

³⁸The change in results for the deterministic model is very similar, and are available upon request.

estimate with common preferences. The reason is because the estimates of b and β also differ across the two groups, which also affect the labor supply profile over the life cycle. However, the model fit measured as the sum of squared errors is considerable worse than the model with common preferences. However, the differences are small and if anything it strengthens the finding that the *i.e.s.* is low even when the effects of human capital accumulation are taken into account.

Table 1.3: Parameter estimates for the stochastic model with education specific preferences, targeting age 25-60.

NCD				CD			
γ	0.4818	A	0.1506	γ	0.4825	A	0.2194
b	16.3581	d	0.0304	b	17.3107	d	0.0304
β	0.9530	α	0.3234	β	0.9535	α	0.4498
SSE	0.0540						

Note: Targets based on monthly CPS data from 1979 to 2008. 'NCD' refers to workers without a College degree and 'CD' refers to workers with a College degree. SSE is the sum of squared errors. The simulated targets are based on a draw of 10000 individuals.

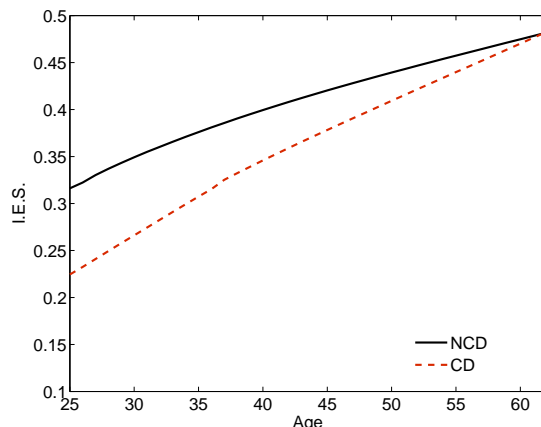
As emphasized above, the estimate of γ is of limited interest when it comes to comparing the intertemporal elasticity of substitution across the two model specifications, as this is also influenced by the other parameters of the model. I therefore use equation (1.16) to compute the *i.e.s.* using the simulated data, and compare the evolution of the *i.e.s.* across the two models. For the model education specific preferences and common age-effect, d , the profiles for the *i.e.s.* looks similar to the ones with common preferences, see figure 1.12. The increase in the *i.e.s.* is common across the two models; for non-college graduates the *i.e.s.* increases more with common preference, 58 percent versus 52 percent with uncommon preferences, whereas for college graduates the *i.e.s.* increases more with uncommon preferences, 108 percent versus 115 percent.

In the estimation above, I have assumed log-utility. However, when facing uncertainty the degree of risk aversion may affects the incentives to insure against this risk, and thus affect labor supply decisions. As the need for insurance is largest for young workers, higher risk aversion leads to higher labor supply when young, and thus the assumption of log-utility may bias the estimates of γ downwards if the degree of risk aversion is considerably higher. In order to test the sensitivity of my results with respect to risk aversion, I estimate the stochastic model using a CRRA utility function

$$u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma},$$

with a relative risk parameter, σ , of 2. The results are presented in table 1.4. As expected, the estimate of γ increases. Notice that the fit, measure as the sum of squared errors, are considerably worse than above. Again, to assess the changes in the intertemporal elasticity of

Figure 1.12: Intertemporal elasticity of substitution over the life cycle with education specific preferences.



Note: Age averages of simulated data.

substitution of a higher risk aversion, I compute the life cycle path of the *i.e.s.*. For non-college graduates, the *i.e.s.* increases by 18 percent which is much smaller compared to the increase for log-utility. For college graduates it increases by 131 percent, compared to 108 percent increase with log-utility. However, as the fit with higher risk aversion is considerably worse, it is difficult to fully compare the estimates of the *i.e.s.* as they depend on the simulated data which is much more similar to the actual data with log-utility.

Table 1.4: Parameter estimates for the stochastic model, with a relative risk aversion of 2. Targeting age 25-60.

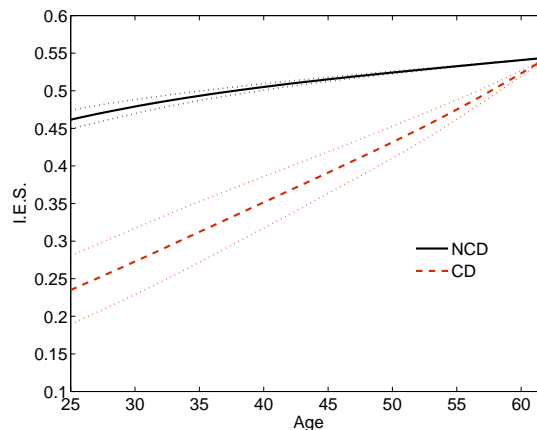
			NCD	CD
γ	0.5440	A	0.1021	0.1995
b	28.4848	d	0.0247	0.0234
β	0.9552	α	0.0990	0.5946
SSE	0.1416			

Note: Targets based on monthly CPS data from 1979 to 2008. 'NCD' refers to workers without a College degree and 'CD' refers to workers with a College degree. SSE is the sum of squared errors. The simulated targets are based on a draw of 10000 individuals.

1.6 Labor income taxation - Welfare analysis

When workers accumulate human capital the impact of transitory wage shocks on hours are dampened, and more so for workers with a high return to human capital accumulation. Thus, also the impact of transitory tax changes are smaller in the model estimated above, compared to a standard model without human capital. In standard models without human capital, the

Figure 1.13: Intertemporal elasticity of substitution over the life cycle with a risk aversion of 2.



Note: Age averages of simulated data. The dotted lines are +/- 2 standard deviation confidence intervals for the *i.e.s.* calculated from the simulated data.

response in hours to transitory wage changes exceeds the response in hours to permanent wage changes. Then, the *i.e.s.*/Frisch elasticity represents an upper bound on the response of hours to permanent tax changes. However, as emphasized by Keane (2012) and Keane and Rogerson (2012) the *i.e.s.* is not the best suited parameter to evaluate the effects of permanent tax policies in models with human capital. First, with human capital the effect of permanent tax changes may exceed the effect of transitory tax changes if the return to human capital accumulation is large, or if the income effect is sufficiently small. Second, in contrast to transitory tax changes, where human capital dampens the effect, with permanent tax changes the role of human capital is to amplify the effect of taxes in the long-run. As Keane puts it, human capital creates a "snowball effect"; increasing taxes permanently decreases today's labor supply, which reduces human capital accumulation. This reduces next periods wages, and thus next periods labor supply, which further reduces human capital accumulation. Thus, using the estimated *i.e.s.* for different age and education groups as an upper bound on the response of hours to permanent changes in taxes may yield too low welfare costs associated tax changes.

Keane (2012) finds that welfare costs of permanent tax changes in a model with human capital are large, and 4 to 7 times larger than in a model with no human capital accumulation. This is both due to the fact that human capital makes permanent tax changes exceed transitory shocks for the youngest and the oldest worker, and because Keane finds that the snowball-effect is very large. I revisit these findings using the model estimated in section 4. There are two key differences between the model here and the model used by Keane (2012). First, Keane uses an estimate of the intertemporal elasticity of substitution for soon-to- retire workers of 3.8, which is the *i.e.s.* estimated by Imai and Keane (2004). This is a very high estimate of the *i.e.s.* compared to the rest of the literature, and about 10 times larger than what I obtain. The welfare costs of permanent tax changes depends crucially on the size of the snowball effect, which depends on the intertemporal elasticity of substitution. Second, Imai and Keane

estimate their model using data on workers between age 20 and age 36. However, as found by Wallenius (2011), the out-of sample performance of the model is poor. In particular, hours declines too sharply after the age of 40, and so does wages. As the production function of human capital features decreasing returns to scale, a too low level of labor supply is associated with a too large change in human capital accumulation when hours change. The model fit of hours and wages in the model estimated above is good for all ages and for both education groups, and I take the good fit of hours and wages as a support of reasonable production function estimates.

Before I turn to the welfare analysis of permanent tax changes, I look at the response of both transitory and permanent shocks in the model estimated above, and compare the findings with Keane (2012). I use the benchmark model estimated in section 4, which assumes log utility. Thus, my results are only directly comparable with parts of the results obtained by Keane, as he mostly uses a lower than unity risk aversion. The effects on labor supply of an unexpected tax increase of 5% occurring at different ages are presented in table 1.5. The first 4 columns looks at the response of hours for college and non-college workers to a 5% temporary tax increase. In the uncompensated case, the tax income is just waste, whereas in the compensated case, tax income is distributed back to the workers in a lump-sum form on a yearly basis. In standard models without human capital, the change in hours to a transitory shock exceeds the change in hours to a permanent shock. With human capital however, changes in hours due to permanent tax changes can exceed the effect of transitory shocks. This is the case if the return to human capital accumulation is sufficiently strong, or if the income effect is small. Let's first compare the transitory and permanent uncompensated tax increase, column 1-2 and 5-6. As expected, with log utility the permanent uncompensated effect is close to zero, except for older ages where the horizon of the tax increase is closer to the transitory increase. Thus, for the uncompensated increase, with log utility, the standard result holds that transitory changes have a larger effect than permanent. With compensated tax increases, permanent tax changes have a larger effect than transitory changes for young workers. And, the effect is strongest for college educated; for non-college educated permanent tax changes have a larger effect on labor supply than transitory until the age of 30, whereas for college educated the effect of permanent tax changes exceed the effect of transitory until the age of 35. This is qualitatively similar to what Keane (2012) finds, which reports the average of all workers. However, I find a smaller difference than Keane at young ages, and I do not find that the permanent effect is larger for older workers as Keane does. Here, the effect of permanent tax changes approaches the effect of transitory changes as workers approaches retirement, but it never exceeds. Thus, using a much smaller estimate of the *i.e.s.*, the result that permanent tax changes may exceed transitory changes is maintained, but I find the magnitude of this effect to be smaller than what Keane finds.

When taxes are permanent, not only does the immediate response of the economy matters, but also, and possibly more important, are the long run effects of a tax change. To evaluate the long run changes, I compute the changes in labor supply over the life cycle of a permanent 5% tax increase at age 25. Then, future wages are not only effected by the tax increase

Table 1.5: Percentage change in labor supply in response to a 5 percent tax increase at the indicated age.

Age	Transitory (unanticipated)				Permanent (unanticipated)			
	Uncompensated		Compensated		Uncompensated		Compensated	
	NCD	CD	NCD	CD	NCD	CD	NCD	CD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
25	-1.33	-0.95	-1.40	-1.04	-0.06	-0.05	-1.57	-1.62
30	-1.43	-1.10	-1.51	-1.23	-0.04	0.10	-1.56	-1.53
35	-1.54	-1.20	-1.61	-1.40	-0.05	0.17	-1.57	-1.49
40	-1.61	-1.50	-1.71	-1.61	-0.10	0.05	-1.59	-1.54
45	-1.71	-1.65	-1.82	-1.76	-0.22	-0.05	-1.64	-1.58
50	-1.79	-1.76	-1.92	-1.90	-0.42	-0.25	-1.70	-1.65
55	-1.88	-1.86	-2.03	-2.02	-0.77	-0.63	-1.82	-1.77
60	-1.93	-1.92	-2.13	-2.14	-1.45	-1.38	-2.03	-2.01

Note: Response in hours to a 5% tax increase is distributed back in a lump-sum form, on a yearly basis. NCD refers to workers without a college degree, whereas CD refers to workers with a college degree.

directly, but also indirectly through lower human capital accumulation due to lower labor supply. This is the snowball effect, which [Keane \(2012\)](#) finds to be very important. The change in hours and pre-tax wages over the life cycle for the log-utility model is given in table 1.6. For comparison, I have also included the changes in hours and wages in the [Imai and Keane \(2004\)](#) model, which assumes a risk aversion of 0.74, taken from [Keane \(2012\)](#). Pre-tax wages falls by much less compared to the Imai and Keane model. This is due to a lower response in hours, which is due to a much lower estimate of the intertemporal elasticity of substitution, and also due to the model fit. In the model by Imai and Keane simulated hours after the age of 40 are substantially lower than in the data. With decreasing returns to scale, this translates into a too large change in human capital production, as the production per unit is substantially larger than for higher levels of labor supply. Thus, it seems that the large snowball effect found by Keane hinges on a large estimate of the *i.e.s.*

By comparing the change in hours for older non-college and college workers in table 1.6 with the ones in the last two columns of table 1.5, it is evident that the change in hours are smaller when the tax change occurred at the beginning of the working life. The snowball effect is apparently not large enough to outweigh the income effect. Although workers are compensated for their tax payments, they are not compensated for the loss of future income due to lower human capital accumulation. Part of the decrease in wages is compensated through higher labor supply, thus reducing the long-run labor supply effect of a permanent tax change. This is in sharp contrast to the findings by Keane, which finds that due to the large snowball effect the reduction in hours at age 60 of a permanent tax increase that started at age 25 is double the effect of a transitory tax increase at age 60.

Given the much smaller snow-ball effect of human capital, I expect to find much lower

Table 1.6: Effects of permanent tax increase on labor supply and wages at different ages. A comparison of the response of the model estimated in section 4.2 with the model of Imai and Keane (2004). Percent.

	Benchmark model				Imai and Keane (2004)	
	NCD		CD		Hours	Wage*
Age	Hours	Wage*	Hours	Wage*	Hours	Wage*
25	-1.57	—	-1.62	—	-2.7	—
30	-1.62	-0.16	-1.65	-0.24	-2.9	-0.4
35	-1.66	-0.32	-1.70	-0.45	-3.2	-0.7
40	-1.70	-0.46	-1.70	-0.64	-3.8	-1.0
45	-1.74	-0.60	-1.74	-0.80	-5.1	-1.3
50	-1.77	-0.72	-1.77	-0.93	-7.9	-2.0
55	-1.80	-0.84	-1.80	-1.05	-13.3	-3.6
60	-1.82	-0.95	-1.82	-1.15	-19.3	-7.5
62/65*	-1.84	-0.99	-1.84	-1.18	-29.2	-11.6

Note: The tax change is a 5 percentage point permanent tax increase which is distributed back in a lump-sum form, on a yearly basis. The effects from the model by Imai and Keane (2004) are taken from Keane (2012).

* Reduction in pre-tax wages

welfare costs of tax changes compared to Keane (2012). I use two measures to evaluate the long-run welfare costs of taxes. Since I have a dynamic model from age 25 to death, it is natural to look at the change in the life time utility at age 25, measured in consumption equivalents. I also look at the change in life time consumption, discounted to age 25. I keep the assumption that taxes are distributed back in a lump-sum manner. In response to a 5 percentage points permanent tax increase welfare, measured in consumption equivalents, is reduced by about 0.04 percent for workers with and without a college degree, respectively, see table 1.7. The reduction in life time consumption is much larger, where consumption falls by 1.99 percent for workers without a College degree and 2.21 percent for College graduates. Thus a substantial part of the drop in consumption is compensated by an increase in the utility from leisure.

Table 1.7: Welfare losses and consumption losses of a 5 percentage points tax increase

	Benchmark model		No Human Capital
	NCD	CD	($A = 0, \delta = 0$)
ΔC^*	-0.04	-0.04	-0.04
ΔC	-1.99	-2.21	-1.50

Note: The tax income is distributed back in a lump-sum form, on a yearly basis. ΔC is the change in life-time consumption, discounted to age 25. ΔC^* is the welfare loss measured in consumption equivalents.

Welfare losses, measured by the fall consumption, increases by 33 percent higher for workers without a college degree and by 47 percent higher for College graduates compared to the model with no human capital. Comparing welfare losses in consumption equivalents, the welfare loss is the same whether or not workers accumulate. This is because increase utility from leisure compensates for a large fraction of the consumption drop. The increase in welfare loss is significantly lower than what Keane finds, where human capital increases the loss by 4-7 times. For the sake of comparison with Keane, the welfare costs reported are the long-run costs, and do not include costs along the transition. However, I expect the changes along the transition to be similar to the long-run costs, as the response of hours in table 1.5 and 1.6 are very similar. Potentially more importantly, however, is the failure to take into account the welfare costs of a reduction in human capital accumulation. However, this requires a general equilibrium model. But, as I find the reduction in human capital of a 5 percentage points permanent tax increase to be relatively modest, I expect that the welfare costs of this reduction in human capital is modest.

1.7 Conclusion

In this paper I argue that the average *i.e.s.* is low, and comparable with micro estimates, even in the presence of human capital accumulation. This is due to the findings that (i) a large share of the increase in the extensive margin early in the working life should not be included as changes in optimal labor supply, and (ii) human capital accumulation implies a state-dependent intertemporal elasticity of substitution, which makes the average elasticity lower than the estimated utility parameter. First, when estimating the *i.e.s.* there is an important distinction to be made between voluntary and involuntary quits. This is because involuntary quits are not a choice by the worker, and should therefore not be included in the measure of labor supply when estimating the *i.e.s.*. Using monthly data on labor market transitions taken from the CPS I show that the majority of unemployment spells are involuntary. Moreover, I find that most of the changes in the extensive margin of labor supply occurs early in life, and is due to either involuntary unemployment or due to a sample effect caused by students leaving university and starting to work throughout the year. Second, when workers accumulate human capital the *i.e.s.* is no longer only a function of the preference parameters, but a state-dependent variable that crucially depends on the return to human capital accumulation. I identify two import sources of heterogeneity with respect to return to human capital accumulation; age and education, and show that the *i.e.s.* is increasing in age and decreasing in education.

To quantify the importance of the state-dependency of the *i.e.s.* and the empirical measure of labor supply, I estimate a life cycle model with endogenous labor supply along the intensive margin, human capital accumulation through learning by doing and wage uncertainty, using cohort data on white males from CPS for workers with and without a college degree. I target only the intensive margin of labor supply, and find an estimate of the *i.e.s.* for soon-to-retire-workers of 0.45. However, there are significant differences across age and education;

the estimate of the *i.e.s.* for workers aged 25 is 0.22 and 0.29 for workers with and without a College degree, respectively. Second, at young ages non-college workers have 32 percent higher *i.e.s.* than young college educated. Using population weights calculated from the CPS, and a share of 1/3 college graduates, the average *i.e.s.* in the population is 0.35. Thus, the average elasticity is well below the estimate of the *i.e.s.* for workers soon-to-rotate, which is identical to the estimate of the (inverse) curvature of the marginal disutility of labor. The increase in the *i.e.s.* over the life cycle is however significantly lower than what Imai and Keane finds in a similar model, when looking at uncompensated changes in labor supply.

I perform robustness checks on two of my key assumptions, namely the assumption of common preferences across education groups and log-utility of consumption. Relaxing these assumptions yields small changes in the estimates, and the key conclusions are not altered; the estimate of the average intertemporal elasticity of substitution is low, and the *i.e.s.* increases significantly over the life cycle.

Finally, I revisit the findings by Keane (2012), which argue that once the effects of human capital is taken into account the long-run welfare costs of tax changes are large, and more than 4-7 times larger than in conventional models. This is because human capital amplifies the long-run effect of taxes through a "snowball-effect"; lower labor supply today reduces human capital accumulation, and thus reduces future wages which again reduces future labor supply. Using the model estimated above, I find that the importance of the snowball-effect hinges on the high estimate of the *i.e.s.* used by Keane in the analysis (3.8); The welfare costs of a permanent 5 percentage points tax increase in the model estimated above, with an average *i.e.s.* of 0.35, implies a welfare loss, measured in consumption loss, of 1.99 percent and 2.12 percent for non-college and college workers, compared to a loss of 1.5 percent loss for both education groups in the same model without human capital. So, although human capital do increase the loss of taxation, the difference is much smaller than previously found. The analysis is however, as Keane's, partial equilibrium analysis, which may understate the importance of human capital, as the productivity costs of reduced human capital accumulation is not taken into account.

The state-dependency of the *i.e.s.* and the difference in estimation bias across different samples in terms of age and education indicate that one should be cautious when comparing estimates of the intertemporal elasticity of substitution obtained from different samples with respect to e.g. the age and education distribution. Moreover, the state-dependency of the *i.e.s.* has important policy implications, as the substitutability of labor depends on age and ability to accumulate human capital. Thus, both the age structure of the economy and the education/occupation structure of the economy may matter significantly for the effect of e.g. tax changes on average labor supply. These effects are however not explored here, but are topics for future work.

Appendix

A State-dependent i.e.s.

I define the intertemporal elasticity of substitution as the percentage change in the intertemporal labor supply to a one percent temporary increase in the rental rate on human capital, p_t^h , ($p_j^h = 0, \forall j \neq t$), keeping marginal utility of consumption fixed:

$$i.e.s. = \frac{d\left(\frac{n_t}{n_{t+1}}\right)}{dp_t^h} \frac{p_t^h}{\frac{n_t}{n_{t+1}}} \quad (\text{A.1})$$

Rewriting this yields

$$i.e.s. = \frac{dn_t}{dp_t^h} \frac{p_t^h}{n_t} - \left(\frac{\partial n_{t+1}}{\partial k_{t+1}} \frac{dk_{t+1}}{dp_t^h} + \frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{dh_{t+1}}{dp_t^h} \right) \frac{p_t^h}{n_{t+1}}. \quad (\text{A.2})$$

Without human capital, the last term in parenthesis would have been zero and the intertemporal elasticity of substitution would have been identical to the Frisch elasticity. However, with human capital, also future labor supply responds to changes in today's rental rate, as this affects future wages through today's production of human capital.

I the following I assume, as in the model, that preferences are separable in consumption and leisure, and in time, and that production of human capital is linear in the capital stock, $\frac{\partial^2 G_{t+1}}{\partial h_{t+1}^2} = 0$. Given the functional forms, there are no analytical solutions for the policy functions. I therefore take the total derivative of the first order condition for labor, equation (1.14), imposing that $dh_t = dk_t = 0$:

$$\frac{dn_t}{dp_t^h} = \frac{1}{\left(b \frac{1}{\gamma} n_t^{\frac{1}{\gamma}-1} - \mu_t \frac{\partial^2 G_t}{\partial n_t^2}\right)} \left(u'(c_t) \varepsilon_t h_t + \frac{\partial G_t}{\partial n_t} \frac{d\mu_t}{dp_t^h} \right). \quad (\text{A.3})$$

The derivative of the shadow price on skills with respect to an increase in the current price on skills, is given by

$$\frac{d\mu_t}{dp_t^h} = \beta E_t \left[\left(1 - \delta + \frac{\partial G_{t+1}}{\partial h_{t+1}} \right) \frac{d\mu_{t+1}}{dp_t^h} + \frac{b n_{t+1}^{\frac{1}{\gamma}}}{h_{t+1}} \frac{dn_{t+1}}{dp_t^h} \right], \quad (\text{A.4})$$

where I have used the first order condition for n_{t+1} and the linearity of G_{t+1} in h , so that $h_t \frac{\partial^2 G_{t+1}}{\partial h_{t+1} \partial n_{t+1}} = \frac{\partial G_{t+1}}{\partial n_{t+1}}$.

The total derivative of future variables depends only on human capital, and not on future capital stocks. The proof for this is the following: Using the budget constraints, and the law of motion for human capital, we know that

$$h_{t+2} \left(1 - \frac{dk_{t+2}}{dk_{t+1}} \right) \frac{dn_{t+2}}{dk_{t+2}} = \left(\frac{dk_{t+3}}{dh_{t+2}} - n_{t+2} \right) \frac{dG_{t+1}}{dn_{t+1}} \frac{dn_{t+1}}{dk_{t+1}}. \quad (\text{A.5})$$

Then, if for any t : $\frac{dn_t}{dk_t} = 0$, $\frac{dn_t}{dk_t} = 0 \forall t$. Looking at the derivative of the first order condition for labor with respect to capital in period T , $\frac{dn_T}{dk_T}$, this is zero, as $\mu_T = 0$, and given

that $u'(c_t) = 0$ by assumption. Moreover, from the first order condition for labor supply in any period

$$\frac{dn_{t+2}}{dk_{t+2}} = \frac{1}{b^{\frac{1}{\gamma}} n_t^{\frac{1}{\gamma}-1} - \mu_{t+2} \frac{\partial^2 G_{t+2}}{\partial n_{t+2}^2}} \frac{\partial G_{t+2}}{\partial n_{t+2}} \frac{d\mu_{t+2}}{dk_{t+2}}, \quad (\text{A.6})$$

we see that as $\frac{dn_t}{dk_t} = 0 \forall t$, so is also $\frac{d\mu_t}{dk_t} = 0, \forall t$. So, labor supply responds only to human capital (and the rental rate). Hence $\frac{dn_{t+1}}{dp_t^h} = \frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{dh_{t+1}}{dp_t^h}$, and $\frac{d\mu_t}{dp_t^h}$ simplifies to

$$\frac{d\mu_t}{dp_t^h} = \beta E_t \left[\left(1 - \delta + \frac{\partial G_{t+1}}{\partial h_{t+1}} \right) \frac{\partial \mu_{t+1}}{\partial h_{t+1}} + \frac{bn_{t+1}^{\frac{1}{\gamma}}}{h_{t+1}} \frac{\partial n_{t+1}}{\partial h_{t+1}} \right] \frac{dh_{t+1}}{dp_t^h}. \quad (\text{A.7})$$

Moreover, the intertemporal elasticity of substitution simplifies to

$$i.e.s. = \frac{dn_t p_t^h}{dp_t^h n_t} \left(1 - \frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{\partial G_t}{\partial n_t} \frac{n_t}{n_{t+1}} \right) \quad (\text{A.8})$$

Now, one only needs to find $\frac{dn_{t+1}}{dh_{t+1}}$ as a function of $\frac{\partial \mu_{t+1}}{\partial h_{t+1}}$, so that $\frac{d\mu_t}{dp_t^h}$ can be solved recursively. This is obtained from the FOC of labor

$$\frac{dn_{t+1}}{dh_{t+1}} = \frac{1}{\left(b^{\frac{1}{\gamma}} n_{t+1}^{\frac{1}{\gamma}-1} - \mu_{t+1} \frac{\partial^2 G_{t+1}}{\partial n_{t+1}^2} \right)} \left(\frac{bn_{t+1}^{\frac{1}{\gamma}}}{h_{t+1}} + \frac{\partial G_{t+1}}{\partial n_{t+1}} \frac{d\mu_{t+1}}{dh_{t+1}} \right) \quad (\text{A.9})$$

Then, the *i.e.s.* is obtained from solving the following system of equations recursively

$$\begin{aligned} ies_t &= \frac{dn_t p_t^h}{dp_t^h n_t} \left(1 - \frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{\partial G_t}{\partial n_t} \frac{n_t}{n_{t+1}} \right) \\ \frac{dn_t p_t^h}{dp_t^h n_t} &= \gamma \frac{1}{\left(\Upsilon_t - \gamma \left(\frac{\partial G_t}{\partial n_t} \right)^2 \Psi_t \right)} u'(c_t) \varepsilon_t h_t \frac{p_t^h}{n_t}, \\ \frac{dn_t h_t}{dh_t n_t} &= \frac{dn_t p_t^h}{dp_t^h n_t} \frac{1}{u'(c_t) \varepsilon_t} \left(\frac{bn_t^{\frac{1}{\gamma}}}{h_t} + \frac{\partial G_t}{\partial n_t} \Psi_t \frac{h_{t+1}}{h_t} \right), \\ \Psi_t &\equiv \beta E_t \left\{ \frac{n_{t+1}}{h_{t+1}} \left[\frac{h_{t+2}}{h_{t+1}} \frac{1}{\frac{\partial G_{t+1}}{\partial n_{t+1}}} \left[\Upsilon_{t+1} \frac{dn_{t+1}}{dh_{t+1}} \frac{h_{t+1}}{n_{t+1}} - bn_{t+1}^{\frac{1}{\gamma}-1} \right] + \frac{bn_{t+1}^{\frac{1}{\gamma}}}{h_{t+1}} \frac{dn_{t+1}}{dh_{t+1}} \frac{h_{t+1}}{n_{t+1}} \right] \right\} \\ \Upsilon_t &\equiv bn_t^{\frac{1}{\gamma}-1} - \gamma \mu_t \frac{\partial^2 G_t}{\partial n_t^2}. \end{aligned}$$

In the estimated models above $\gamma \left(\frac{\partial G_t}{\partial n_t} \right)^2 \Psi_t \approx 0$, and $\frac{\partial n_{t+1}}{\partial h_{t+1}} \frac{\partial G_t}{\partial n_t} \frac{n_t}{n_{t+1}} \approx 0$, so the *i.e.s.* simplifies to

$$ies_t \approx \gamma \frac{1}{bn_t^{\frac{1}{\gamma}-1} - \gamma \mu_t \frac{\partial^2 G_t}{\partial n_t^2}} u'(c_t) \varepsilon_t h_t \frac{p_t^h}{n_t} \quad (\text{A.10})$$

B Additional estimation results

This appendix shows some additional estimation results. First, I show the estimation results for the model without uncertainty when I fix α at 0.2, 0.4, and 0.6. This is to ensure that α is indeed identified in the approach above. Indeed, the sum of squared errors shows some variability for the different value of α , and the model with best fit is when the α 's are constrained to be 0.4, which is close to the estimated values above ($\alpha_{NCD} = 0.48$, $\alpha_{CD} = 0.47$), see table B.1. Moreover, all models estimate a low value of γ , and the dispersion is estimates are low.

Table B.1: Parameter estimates with pre set values of α .

	$\alpha = 0.2$		$\alpha = 0.4$		$\alpha = 0.6$	
γ	0.4076		0.4612		0.4778	
b	21.2701		18.4737		18.9417	
β	0.9628		0.9576		0.9531	
	NCD	CD	NCD	CD	NCD	CD
A	0.0838	0.2129	0.1043	0.2457	0.1301	0.2876
d	0.0170	0.0354	0.0184	0.0348	0.0198	0.0348
SSE	0.0137		0.0084		0.0128	

Note: Estimations of the model without uncertainty.

As an alternative approach, I also estimate the model assuming a common age-effect in the production of human capital. The results are given in table B.2, and again confirms that γ is low and similar to the value estimated in section 4.2 ($\gamma = 0.45$). However, the model fit is considerably worse.

Table B.2: Parameter estimates with common d .

		NCD	CD
γ	0.4790	A 0.1574	0.2160
b	16.8262	d	0.0311
β	0.9538	α 0.3416	0.4034
SSE	0.0620		

Note: Estimations of the model with uncertainty.

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2 Optimal Labor Market Policies

- The Importance of Heterogeneous Returns to Labor Market Experience

2.1 Introduction

A central topic in public finance is how to provide unemployment insurance (UI) to the population without distorting search incentives. Search incentives are typically distorted due to a moral hazard problem arising because search effort by unemployed workers are unobservable to the social planner. Moreover, if the government does not have access to lump-sum taxation, and for example, if labor income taxes are used to finance the UI, taxes also distorts the search effort as taxes widens the wedge between the social gain of re-employment and the private gain.¹

In this paper, I argue that both the *moral hazard problem* and the distortionary effects of labor income taxes on search effort, which I will refer to as a *tax distortion problem*, greatly depends on the assumptions about wage growth over the life cycle. The literature on optimal UI typically assumes that wages evolves exogenously when employed.² This is in stark contrast to the empirical literature, which has extensively documented a positive relationship between contemporaneous labor effort and future wages.³ Given this evidence, our starting point is a ‘learning-by-doing’ framework, where current labor hours increase future productivity.

A positive return to labor market experience has an important effect on the moral hazard problem of UI for young workers as shown by [Michelacci and Ruffo \(2011\)](#). In particular, it lowers the moral hazard problem associated with UI as young workers have a strong private incentive to search for a job to accumulate high return human capital. Whereas the moral hazard problem traditionally has been viewed as the main cost associated with UI, the presence of a career-effect substantially increases the social costs associated with tax distortions, which are created by the need to finance the UI and other expenses. With a career-effect, taxes not only reduces the private return of re-employment by lowering after-tax

¹Note that any tax, including lump-sum taxes, which is specific to employed workers will distort the search effort decision.

²For early contributors to this literature, see e.g. [Shavell and Weiss \(1979\)](#) and [Hopenhayn and Nicolini \(1997\)](#).

³See e.g. [Blundell and Macurdy \(1999\)](#) and the references therein.

wages but also by reducing the return to human capital accumulation.⁴ The latter is important as contemporaneous distortions of search effort has long lasting effects on future productivity and wages through both a larger depreciation and reduced accumulation of human capital.⁵ And, the higher the tax the larger is the gap between the gross return to human capital, which is the social return to human capital accumulation, and the after-tax return to human capital accumulation, which is the private return. Thus, whereas search effort may respond little to changes in benefits, as the moral hazard problem is low, search effort may be substantially below the optimal level due to the distortionary effects of labor income taxes.

Both the moral hazard problem and the tax distortion problem are likely to change substantially over the life cycle, as the return to human capital accumulation and the productivity level change over the life cycle. Moreover, as different groups of the population face different returns to human capital accumulation, the problems most likely also vary across the population by e.g. the level of education.

The goal of this paper is to measure the magnitude of the moral hazard problem and the tax distortion problem associated with US labor market policies, taking the effects of (heterogeneous) labor market experience into account. In particular, I want to assess (i) if unemployed workers, given the US labor market policies, on average search enough from a social perspective, (ii) if there are any differences between age and education groups, and (iii) what is the relative importance of moral hazard and the distortionary effects of taxes. To this end, I develop a life cycle model which features unemployment, endogenous search effort, and human capital accumulation (learning-by-doing) when employed and human capital depreciation during unemployment. To obtain the deviation between the socially optimal search effort and the search effort exerted by unemployed workers I proceed in two steps. First, I estimate the model by indirect inference methods to match US data in the period 1979 to 2008, both in terms of key variables and labor market policies. I split the sample into three education groups; low (less than High School), medium (High School degree and some College) and high (College degree), and allow for education and age specific production of human capital, job separation probabilities and job finding probabilities. Looking at the profile of real wages over the life cycle, the education groups represent three different degrees of the return to human capital accumulation: no, medium and high return. Second, I compute the education specific optimal contract provided by a planner who maximizes workers utility under the assumption of unobservable search effort. By comparing the search effort of unemployed workers in the benchmark model with the search effort specified in the optimal contract, I obtain a measure of the deviation from the optimal search effort by all education and age groups.

⁴For a thorough discussion of tax policies and human capital formation see e.g. [Heckman et al. \(1998\)](#) and the reference therein.

⁵The distortionary effects of labor income taxes on the human capital accumulation of employed workers are not studied here. The distortionary effects on search effort presented here are thus a lower bound, as they do not take into account future labor supply effects of reduced human capital accumulation.

A comparison of search effort in the optimal contract with the search effort in the estimated model yields three main findings: First, the deviation of search effort from the optimal level is inversely related to the return to experience.⁶ That is, the deviation of search effort is increasing in age, whereas the return to experience is decreasing in age. And, the deviation of search effort is decreasing in education whereas the return to experience is increasing in education. Under the benchmark specification, I find that search effort on average is 21, 11.5 and 9.5 percent lower than the socially optimal level for workers with low, medium and high education, respectively. Moreover, whereas the deviation is constant over the life cycle for the low educated, who have zero return to experience, the deviation increases from about 8 percent (6 percent) at age 25 to 14 percent (13 percent) at age 60 for workers with medium (high) education. The increase over the life cycle is mainly due to an increase in the moral hazard problem, and, to a lesser extent, an increase in the labor tax distortions.

Second, the main social costs associated with unemployment insurance for workers with a positive career-effect are not due to moral hazard problems, but are due a labor income tax needed to finance government expenses, that distorts search effort and thus human capital accumulation. I isolate the importance of moral hazard by comparing the optimal contract with the search effort exerted by workers who face no taxes, as tax distortions vanish if taxes are zero. Note that the measure of the moral hazard problem is a relative measure, and only takes into account the "excess" moral hazard problem relative to the optimal contract. However, under the reasonable assumption of unobservable search effort, the optimal contract is a natural benchmark. For highly educated workers the moral hazard problem is close to zero for young workers and accounts for about 25 percent of the total deviation from the optimal contract for older workers. For workers with medium education the moral hazard problem accounts for below 20 percent of the total deviation for young workers and increases to about 45 – 50 percent for older workers. The importance of moral hazard is constant at 70 percent for low educated workers. Hence, estimates of the moral hazard costs for younger workers with medium to high education may be informative about how a small change in unemployment insurance affect search effort, but it is of limited use to measure the degree to which search effort deviates from the socially optimal effort.

And, third, the deviation from optimal search effort increases in the degree of tax progressivity and decreases in the degree of benefit regressivity. When replacing the benchmark tax function, which features some progressiveness, with a linear tax, the deviation from optimal search effort falls by an average of 1.2 percentage points for workers with a High School degree and some College, and by 1.6 percentage points for College graduates.⁷ The effect is however largest for young workers. When introducing a maximum value on per period benefits, calibrated to match the US system, the replacement rate becomes regressive for

⁶Throughout the paper I will, for simplicity, refer to the search effort specified by the optimal contract as the optimal search effort. As that is the search effort that is optimal under the realistic assumption that search effort is unobservable to the planner. However, this is only the constrained optimal effort as welfare would be improved if effort was observable.

⁷Workers without a High School diploma falls within the first tax bracket, and face a linear tax also in the benchmark policy scheme.

income levels where the maximum benefit binds. For College graduates, where the effect of maximum benefits is largest, the deviation from optimal search effort falls from an average of 9.9 percent to an average of 3.8 percent. And, the deviation from optimal effort is then larger for younger workers compared to older workers as young workers now face more generous UI than older workers. For workers with a High School degree and some College the effect is smaller, with a decrease in the average deviation from 11.5 to 9.5 percent. Also for this group is the effect strongest for older workers, but the deviation is still increasing with age.

The paper is related to the literature on the optimal design of labor market institutions when search effort is unobservable started by [Hopenhayn and Nicolini \(1997\)](#), and which has been extended to include several features also present in this paper.⁸ This literature typically considers an initially unemployed worker with employment as an absorbing state and with a constant re-employment income. In contrast, the main features of the model used here are heterogeneous human capital accumulation/depreciation across age and education, recurrent unemployment spells, and a life cycle dimension. These issues has been separately addressed in the existing literature, but has to my knowledge not been analyzed jointly. [Hopenhayn and Nicolini \(2009\)](#) introduces recurrent unemployment spells and focus on employment history contingent benefits. [Sopraseuth et al. \(2007\)](#) includes a life cycle dimension and argues that re-employment taxes are less effective in a life cycle model due to the shorter horizon. Recently, human capital has been included, see e.g. [Pavoni \(2009\)](#) which analyses the effects of deterioration of job opportunities due to human capital depreciation on the optimal contract.

In a more closely related paper, [Michelacci and Ruffo \(2011\)](#) analyses moral hazard problems in a life cycle model similar to the one presented here.⁹ Using US data they show that the moral hazard problem of young workers are smaller compared to the problem for older workers. They argue that because the moral hazard problem is mild for younger workers, whereas the need for insurance is substantial, it is welfare improving to increase UI for young workers and decrease it for older workers. And, by introducing an age-dependent benefit and tax schedule they move the economy close to the first best. The analysis presented here extends the study by Michelacci and Ruffo by introducing heterogeneity across education groups. Taking taxes as given in the benchmark model, I show that the search effort for all ages and education groups lies well below the effort set in the optimal contract due to the distortions created by labor income taxes. The findings in this paper thus complements the results by Michelacci and Ruffo, and shows that unless major labor income tax reforms are undertaken at the same time as the UI benefits are increased for young workers, an increase in benefits for young workers will widen the gap between the search effort exerted and socially optimal search effort. Moreover, I find large differences in the optimal contract offered to the three education groups, as their career-effects varies substantially. Whereas the average replacement rate is falling with age and the average tax rate is increasing in age for the two highest education groups, the average replacement rate and tax rate is constant across age

⁸See also [Pavoni and Violante \(2007\)](#), [Shimer and Werning \(2008\)](#), [Rendahl \(2007\)](#), and [Pavoni et al. \(2013\)](#).

⁹Note that in contrast to the model presented here, [Michelacci and Ruffo \(2011\)](#) assumes that young workers are credit constrained. Thus, labor market policies which shifts income from older ages to young ages are particularly welfare improving in their set-up.

for the low educated group. This reflects the wage patterns of the education groups and the consumption smoothing motive of the planner. Thus, implementing the policy proposed by Michelacci and Ruffo, where benefits are very generous for young workers and very low for older workers, do not seem optimal for low educated workers. The results presented below indicates that any implementation of the optimal contract should not only take age differences into account, but also differences in career-effects.

The paper is also related to the literature which empirically measures the moral hazard problem. Typically, moral hazard is measured by the response of unemployment duration to benefits.¹⁰ Both Meyer and Mok (2007) and Michelacci and Ruffo (2011) find that the elasticity of unemployment duration to benefits is close to zero for young workers, whereas the elasticity is much larger for older workers. The analysis below supports a low moral hazard costs for young High School graduates, but finds a constant moral hazard problem for workers with less than High School. Moreover, I find that although social costs associated with moral hazard are low there could still substantial deviation from the optimal search effort for unemployed workers due to the tax distortion problem.

The paper proceeds as follows; Section 2 explains the model and the optimal contract offered by a benevolent planner. Section 3 presents the estimation results obtained using indirect inference methods, and section 4 discusses the deviation of search effort in the model compared to the search effort specified in the optimal contract. The optimal contract is discussed in more detail in section 5, and finally section 6 concludes.

2.2 Model

I first present the benchmark model before I discuss the optimal contract offered by the planner which does not observe the costly search effort exerted by unemployed workers.

2.2.1 Benchmark model

This section presents the benchmark life-model used in the policy analysis below. The key model features are (i) costly search effort of unemployed, (ii) human capital accumulation through learning by doing and (iii) a finite life span. As the paper studies optimal unemployment schemes, unemployment and costly search effort are natural ingredients. Endogenous wage growth due to human capital accumulation is important as it affect the search elasticity w.r.t. to UI, as shown by Michelacci and Ruffo (2011).¹¹ Finally, a finite life span is important as both the need for insurance against unemployment shocks and the importance of the human capital accumulation varies substantially with age.

The model is a discrete-time life cycle model for a finitely lived worker. Workers live for $t_w + t_r$ periods, where the first t_w periods are spent working whereas the last t_r are spent in

¹⁰See Chetty (2008) for a discussion of why the elasticity of unemployment duration to benefits may overestimate the moral hazard problems due to liquidity constraints.

¹¹The human capital accumulation also affects the elasticity of labor supply with respect to taxes, as shown by e.g. Imai and Keane (2004), Keane (2011) and in chapter 1 of this thesis. However, to keep the analysis simple, labor supply is assumed to be inelastic here. For more details, see the text.

retirement. The agent has separable preferences over consumption, c , and search effort, e , given by

$$\mathbb{E}_t \sum_{t=0}^{t_w+t_r} \beta^t [u(c_t) - g(e_t)], \quad (2.1)$$

I assume that $u(\cdot)$ is strictly increasing and strictly concave, whereas $g(\cdot)$ is strictly increasing and strictly convex. Both are assumed to be continuously differentiable. In any period, within the working age, the worker could either be unemployed, $\varepsilon = 0$, or employed, $\varepsilon = 1$. If the worker is employed he supplies a fixed amount of hours, and receives an hourly wage equal to his productivity level which is determined by the human capital level, h . The law of motion for human capital for employed and unemployed workers are given by

$$h_{t+1} = G(h_t, a_t), \text{ if } \varepsilon_t = 1, G_h > 0, \quad (2.2)$$

$$h_{t+1} = (1 - \delta^h)h_t, \text{ if } \varepsilon_t = 0, 0 \leq \delta^h < 1, \quad (2.3)$$

where a_t is the age of the worker at time t . The effect of age on the production of human capital is not restricted to be positive or negative in the theoretical model, but will be estimated below. By assumption, unemployed workers are not producing human capital.¹²

Workers can save and borrow in a risk-less asset, k_t . The intertemporal budget constraint for the working periods is given by

$$c_t + k_{t+1} \leq (1 + r)k_t + \varepsilon_t \tau(h_t) + (1 - \varepsilon_t)B(h_t), \quad \varepsilon_t \in \{0, 1\}, \quad \forall t \leq t_w, \quad (2.4)$$

where r is the interest rate. Unemployed workers receive unemployment benefits, $B(h_t)$, which is a function of foregone earnings.¹³ The after tax income is given by the function $\tau(h_t)$, which allows for progressive taxation. Note that (i) the tax distortions in the model arise from the endogeneity of wages and (ii) it only distorts the search effort decision of workers. This is convenient as the focus of the paper is on distortions of search effort. Note however that it implies that the distortions found are to be seen as a lower bound: if labor supply was elastic, taxes would also distort the accumulation of human capital of employed workers, of course in addition to distorting the labor-leisure choice. Thus, the wedge between the private cost of unemployment and the social cost of unemployment would be even larger.

The timing of the model is as follows: at the end of the period $t - 1$ a fraction δ_t of the jobs separate and the workers becomes unemployed. During period t unemployed workers exert costly search effort to find a job, which is productive from the beginning of period $t + 1$. The job finding probability is given by the function $\pi_e(e_t, a_t)$, which is increasing in effort, $\pi_e(e_t, a_t) > 0$. The effect of age is left unsigned for now, and will be estimated below.

¹²This is of course a stark assumption, since many unemployed attend job training courses etc. However, it seems reasonable that employed on average have a higher human capital accumulation than unemployed.

¹³To reduce the state space I assume that benefits are a function of this periods foregone earnings, and not of last periods earnings.

Employed workers maximize utility subject to the budget constraint, equation (2.4), and the law of motion for human capital, equation (2.2). The recursive formulation is given by

$$V^e(k_t, h_t, t) = \max_{c_t^e, k_{t+1}} \{u(c_t^e) + \beta((1 - \delta_t)V^e(k_{t+1}, h_{t+1}, t + 1) + \delta_t V^u(k_{t+1}, h_{t+1}, t + 1))\} \quad (2.6)$$

s.t

$$c_t^e = (1 + r)k_t + \tau(h_t) - k_{t+1}, \quad (2.7)$$

$$h_{t+1} = G(h_t, a_t), \quad (2.8)$$

$$a_t = f(t), \quad (2.9)$$

$$k_{t_w+t_r+1} = 0, \quad (2.10)$$

where $f(\cdot)$ is the function that maps time to age.

Unemployed workers maximizes utility subject to the budget constraint, equation (2.4), and the law of motion for human capital for unemployed workers, equation (2.3). The recursive formulation is given by

$$V^u(k_t, h_t, t) = \max_{c_t^u, k_{t+1}, e_t \in [0,1]} \left\{ u(c_t^u) - g(e_t) + \beta \left(\begin{array}{l} \pi_e(e_t, a_t)V^e(k_{t+1}, h_{t+1}, t + 1) \\ +(1 - \pi_e(e_t, a_t))V^u(k_{t+1}, h_{t+1}, t + 1) \end{array} \right) \right\} \quad (2.11)$$

s.t

$$c_t^u = (1 + r)k_t + B(h_t) - k_{t+1}, \quad (2.13)$$

$$h_{t+1} = (1 - \delta^h)h_t, \quad (2.14)$$

$$a_t = f(t), \quad (2.15)$$

$$k_{t_w+t_r+1} = 0. \quad (2.16)$$

When workers retire, they receive pensions equal to a fraction π of their actual (or counterfactual) earning in the last working period, $t = t_w$. The value of retirement, R , is given by

$$R(k_t, h_t) = \frac{1 - \beta^{n_r}}{1 - \beta} u \left(\tau(\pi h_{t_w}) + \frac{1 - \beta}{1 - \beta^{n_r}} (1 + r)k_{t_w+1} \right). \quad (2.17)$$

2.2.2 Optimal contract

Consider a planner who must design an optimal unemployment insurance program and a tax program to finance the UI system (and pensions). The planner is assumed to be risk neutral and discounts at the same rate as the workers. When the planner cannot observe search effort the provision of unemployment insurance distorts search incentives and creates moral hazard problems. I assume that the planner can observe the worker's age, human capital level (which is equivalent to the labor income), and her asset position. The planner can also observe if agents have lost their job or not, and I assume that all job-losses are involuntary. I thus abstract from all issues related to eligibility of UI benefits based on whether or not the worker quit the job or was laid off, see [Hopenhayn and Nicolini \(2009\)](#).

I follow the recursive contract theory and characterize the optimal scheme using continuation utility as a sufficient statistic for the workers history. Let v_t^j be the discounted utility promised to the worker in period t if the worker is employed, $j = e$, or if the worker is unemployed, $j = u$. Given the states (t, h_t, v_t^e) the planner chooses taxes, T , which may be negative, and continuation utilities for both states, $v_{t+1}^{e/u}$, such that they minimize the total discounted costs, $C^e(t, h_t, v_t^e)$:

$$C^e(t, h_t, v_t^e) = \min_{T_t, v_{t+1}^e, v_{t+1}^u} -T_t + \beta [(1 - \delta_t)C^e(t+1, h_{t+1}, v_{t+1}^e) + \delta_t C^u(t+1, h', v_{t+1}^u)] \quad (2.18)$$

s.t.

$$v_t^e \leq u(h_t - T_t) + \beta [(1 - \delta_t)v_{t+1}^e + \delta_t v_{t+1}^u], \quad (2.19)$$

$$h_{t+1} = G(h_t, a_t), \quad (2.20)$$

subject to the promise keeping constraint, equation (2.19), and the law of motion for human capital, equation (2.20).

The problem of the employed is trivial, as there are no information problems. For workers who have lost their jobs however, the planner face the trade-off between (unemployment) insurance and (search) incentives. The principal sets the unemployment benefit, B_t , and the continuation utilities for both states, $v_{t+1}^{e/u}$, such that they provide incentives to exert the optimal amount of effort, e_t^* , and at the same time minimize the cost function, $C^u(t, h_t, v_t^u)$. The minimization problem for job searchers is given by

$$C^u(t, h_t, v_t^u) = \min_{\substack{B_t, e_t, \\ v_{t+1}^e, v_{t+1}^u}} B_t + \beta \left[\begin{array}{l} \pi(e_t, a_t)C^e(t+1, h_{t+1}, v_{t+1}^e) \\ + (1 - \pi(e_t, a_t))C^u(t+1, h_{t+1}, v_{t+1}^u) \end{array} \right] \quad (2.21)$$

s.t.

$$v_t^u = u(B_t) - g(e_t) + \beta [\pi(e_t, a_t)v_{t+1}^e + (1 - \pi(e_t, a_t))v_{t+1}^u], \quad (2.22)$$

$$e_t = \arg \max_{x \in [0,1]} -g(x) + \beta [\pi(x, a_t)v_{t+1}^e + (1 - \pi(x, a_t))v_{t+1}^u], \quad (2.23)$$

$$h_{t+1} = (1 - \delta^h)h_t, \quad (2.24)$$

where equation(2.22) is the promise-keeping constraint for job searchers and equation(2.23) is the incentive compatibility constraint.

Finally, the worker retires at age $t_w + 1$, and the cost of promising utility v^r at retirement is equal to

$$C^r(t, h_t, v_t^r) = \frac{1 - \beta^{n_r}}{1 - \beta} p, \quad (2.25)$$

where p is the constant consumption level after retirement that solves

$$v_t^r = \frac{1 - \beta^{n_r}}{1 - \beta} u(p). \quad (2.26)$$

The maximum utility, v^* , attained by all workers at birth is obtained by solving

$$C^s(1, h_1, v^*) = \tilde{c}, \quad (2.27)$$

where \tilde{c} is the exogenously set total net cost of the policies, discounted to period 1.

Some Characterization of the optimal contract

The first order conditions for employed workers are given by

$$\lambda_t^{PK_e} = \frac{1}{u'(h_t - T_t)}, \quad (2.28)$$

$$C_{v_{t+1}^e}^e(t+1, h_{t+1}, v_{t+1}^e) = \lambda_t^{PK_e}, \quad (2.29)$$

$$C_{v_{t+1}^u}^s(t+1, h_{t+1}, v_{t+1}^u) = \lambda_t^{PK_e}. \quad (2.30)$$

The first order conditions of the problem for the job searchers are given by

$$C_{v_{t+1}^e}^e(t+1, h_{t+1}, v_{t+1}^e) = \frac{1}{u'(B_t)} + \lambda_t^{IC} \frac{\pi'(e_t, a_t)}{\pi(e_t, a_t)} \quad (2.31)$$

$$C_{v_{t+1}^u}^s(t+1, h_{t+1}, v_{t+1}^u) = \frac{1}{u'(B_t)} - \lambda_t^{IC} \frac{\pi'(e_t, a_t)}{1 - \pi(e_t, a_t)} \quad (2.32)$$

$$\lambda_t^{IC} = \frac{\pi'(e_t, a_t)\beta (C^u(t+1, h_{t+1}, v_{t+1}^u) - C^e(t+1, h_{t+1}, v_{t+1}^e))}{(g''(e_t) - \beta\pi''(e_t, a_t) [v_{t+1}^e - v_{t+1}^u])} \quad (2.33)$$

Rearranging the first order conditions and applying the envelope theorem we get the following

Corollary 1 *Assume that e_t is interior, then an optimal contract must satisfy (optimal variables are denoted with an asterisks)*

$$\frac{1}{u'(B_t^*)} = (1 - \pi(e_t^*, a_t)) \frac{1}{u'(B_{t+1}^*)} + \pi(e_t^*, a_t) \frac{1}{u'(c_{t+1}^*)}. \quad (2.34)$$

And, $c_{t+1}^* \geq B_t^* \geq B_{t+1}^*$, which either holds with only strict inequalities or only strict equalities.

Thus, in the optimal contract unemployment benefits will decrease with duration. This is a common property see e.g. [Hopenhayn and Nicolini \(1997\)](#). Moreover, assume log-utility and apply the envelope condition to equation (2.31) and (2.32). Then we get that

$$B_t^* - B_{t+1}^* = \lambda_t^{IC} \frac{\pi'(e_t^*, a_t)}{1 - \pi(e_t^*, a_t)}, \quad e_t \in (0, 1), \quad (2.35)$$

$$c_{t+1}^* - B_t^* = \lambda_t^{IC} \frac{\pi'(e_t^*, a_t)}{\pi(e_t^*, a_t)}, \quad e_t \in (0, 1). \quad (2.36)$$

Both the "consumption-punishment" of not finding a job, $B_t^* - B_{t+1}^*$, and the "consumption-reward" of finding a job, $c_{t+1}^* - B_t^*$, is increasing in the lagrange multiplier of the incentive compatibility, λ^{IC} . λ^{IC} is a measure of the cost of not giving proper incentives to exert the optimal amount of effort, which is increasing in the moral hazard problem of the worker

and the tax distortion problem. Rearranging equation (2.35) and (2.36) gives the following condition for when the planner provides incentive through "consumption-punishment" and through "consumption-reward":

$$c_{t+1}^* - B_t \geq B_t^* - B_{t+1}^* \text{ if } \pi(e_t^*, a_t) \leq \frac{1}{2}. \quad (2.37)$$

This condition states that if the reemployment probability is low the unemployed are mainly given incentives through reward, that is, the increase in consumption if the worker finds a job is larger than the decrease in consumption if the worker stays unemployed. The opposite holds if the reemployment probability is high.

To characterize the optimal contract further, and to compare the optimal contract with the benchmark model, I use a numerical approach. The estimation of the benchmark model is explained in detail in the next section.

2.3 Model estimation

In this section I estimate the benchmark model to obtain the search effort exerted by unemployed US workers, given the existing US labor market policies. Using the estimated parameters from the benchmark model, I can also compute the optimal contract and thus compare the effort exerted with the effort which maximizes social welfare under the assumption of unobservable effort.

The benchmark model is estimated using indirect inference methods, with targets created using monthly data from Consumer Population Survey (CPS) from 1979 to 2008.^{14,15} I generate life cycle profiles for real wages, unemployment rates and weeks of unemployment duration for three education groups. The education groups considered are: less than high school "LTHS/1", High School graduates and those with some college "HS and Some College/2", and College graduates "College+/3". For detailed information about the variables used to generate the targets, see appendix A. One model period is assumed to be 1/8 of a year (1.5 months). This is set as a compromise between the computational burden and the need of a high frequency model to be able to capture the true nature of unemployment spells.

The life cycle values for wages and the unemployment rate are generated taking the average of 14 consecutive cohorts which spans the ages 25-60 with a minimum of 4 observations for each age group.¹⁶ As unemployment duration is not available before 1994, the life cycle values for average weeks of unemployment are the age-averages in the period 1994-2008. I start the sample at age 25 to minimize the sample selection bias associated with schooling, as at age 25 most individuals have finished their studies.¹⁷ The life cycles are displayed in figure 2.1. The targets used in the estimation is five year averages of the variables considered, i.e. the average of 25-29 years, 30-34 years, ..., 50-54 years, and finally 55-60 years.

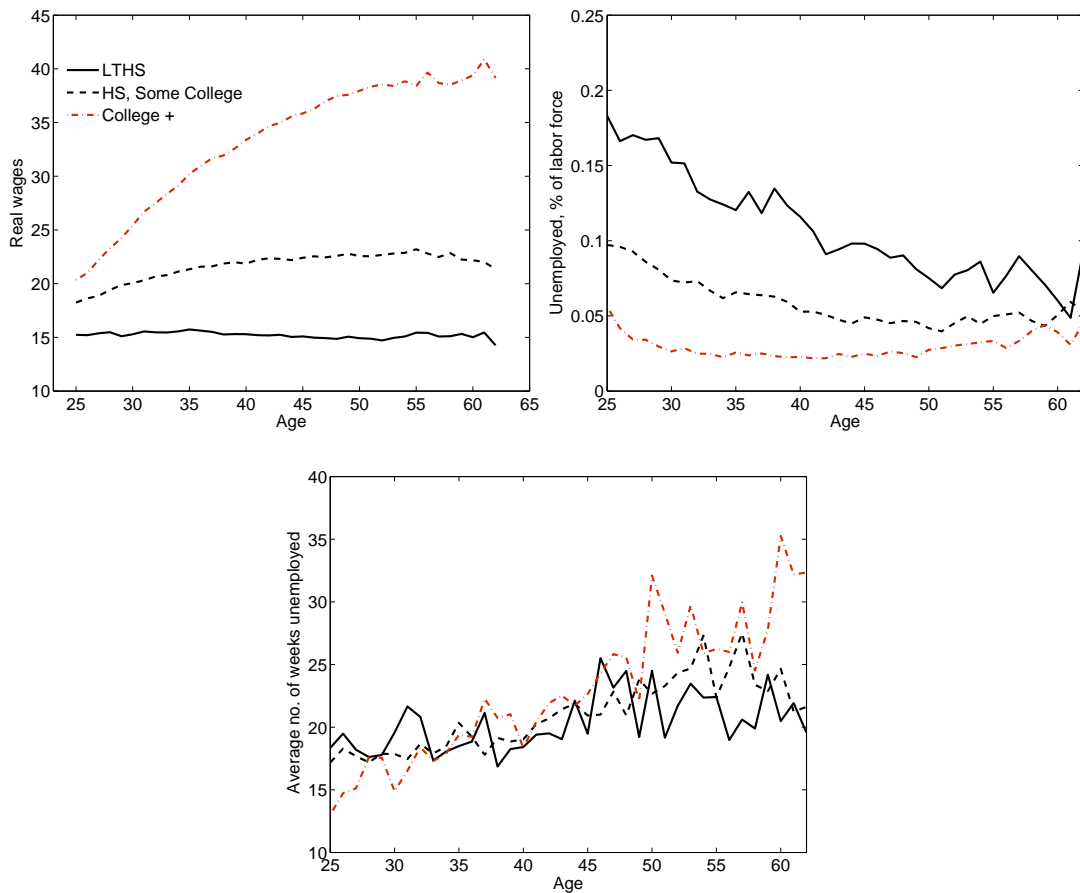
¹⁴The data are from CEPR, Center for Economic and Policy Research. 2006. CPS ORG Uniform Extracts, Version 1.5 . Washington, DC

¹⁵I choose to end the sample in 2008, to not let the financial crisis influence the life cycle pattern.

¹⁶For more information see appendix A.

¹⁷See chapter 1 for a detailed discussion on the sample selection bias associated with schooling.

Figure 2.1: Life cycle profiles for real wages, the unemployment rate and unemployment duration.



Note: Life cycle profiles are obtained from CPS data in the period 1979 to 2008 for real wages and unemployment rates and from 1994 for the unemployment duration. Real wages and unemployment rates are obtained from 14 consecutive cohort, where the first cohort is born in 1944. The life cycle for unemployment duration is constructed by pooling all observations in the period 1994 to 2008.

General specifications All individuals enter the labor force at age 25, retire at age 62, and after 15 years in retirement they exogenously die at age 77.¹⁸ I further assume that all workers have an initial asset level of 40 percent of the initial income, $0.4h_0^i$, and an initial level of human capital equal to the education average of real wages at age 25.¹⁹ I normalize the initial level of human capital by the average real wage for high school dropouts at age 25.

Preferences All education groups are assumed to have the same preferences. The utility of consumption is assumed to be CRRA utility function with a risk aversion of 2. The disutility of effort is given by

¹⁸The age of death in the model is motivated by the life expectancy at age 20 for white males in the US, which is 76.8 years (Source: U.S. National Center for Health Statistics, National Vital Statistics Reports (NVSr), Deaths: Preliminary Data for 2008, Vol. 59, No. 2, December 2010.)

¹⁹The results are similar if I set initial assets to zero. However, as the workers are 25 years old at the beginning it is reasonable to assume that they have some financial assets to help smoothing consumption during an unemployment spell.

$$v(e_t) = b \frac{e_t^{\frac{1}{\gamma} + 1}}{\frac{1}{\gamma} + 1}, \quad b \geq 0, \quad \gamma > 0, \quad (2.38)$$

where the parameters γ and b are estimated. The annual discount factor β is set at 0.9615, to match an annual interest rate of 4 percent.

Production technology Human capital is produced according to a simple technology:

$$G^i(h_t, a_t) = (1 - \delta^h)h_t + A^i \exp(-da_t)h_t, \quad A, d \geq 0, \quad i \in \{1, 2, 3\}. \quad (2.39)$$

which is linear in input: the current level of human capital, and where $A \exp(-da_t)$ is the age-dependent productivity parameter. If d is positive, human capital accumulation will be more demanding with age. I assume that A is an education specific parameters, whereas the effect of age on the production of human capital, given by d , is common across education groups. As real wages are near constant over the life cycle for workers in the first education group, see figure 2.1, I assume that they do not produce any human capital when employed, and set $A_1 = 0$. The annual rate of depreciation of human capital experienced by unemployed workers, δ^h , is set to 3 percent for workers with a High School degree, and zero for High School dropouts. This is in line with micro evidence on the wage costs of labor market intermittency provided by [Kim and Polachek \(1994\)](#), which find that the annual rate of depreciation is between 2-5 percent when controlling for unobserved heterogeneity and endogeneity issues. The parameters of the production function are identified by the real wage targets.

Separation rate I assume that the separation rate decreases with age according to the following expression

$$\delta_t = \delta_{0,i} 25^{\delta_1} a_t^{-\delta_1}, \quad i \in \{1, 2, 3\}, \quad (2.40)$$

where $\delta_{0,i}$ is the separation rate at age 25 for education group i , and δ_1 determines how much and how fast the separation rate falls over the life cycle. In order to be parsimonious about the number of parameters to estimate, I assume that δ_1 is common to all education groups.

Job finding probability The probability of finding a job is given by

$$\pi(e_t, a_t) = 25^{\xi_i} a_t^{-\xi_i} e_t, \quad \xi \geq 0, \quad i \in \{1, 2, 3\}, \quad \xi_2 = \xi_3. \quad (2.41)$$

Again, to be parsimonious I assume that the parameters of the job finding probability function are the same for the two highest education levels. For a given age, the probability increases linearly in search effort.²⁰ For a given search effort the job finding probability decreases with age at a decreasing rate, governed by the size of ξ . This is to capture the increase in unemployment duration over the life cycle, see figure 2.1, which is particularly pronounced for the two highest education groups. Moreover, it is in line with micro evidence on the job finding and the job separation probability over the life cycle: [Johnson and Mommaerts \(2011\)](#) find that not only does the job separation probability decreases with age, also the job finding probability decreases with age. Both the parameters of the separation function ($\delta_{0,1}, \delta_{0,2}, \delta_{0,3}$

²⁰Alternatively, one could assume that disutility of effort is linear and assume an increasing, concave function for the job-finding probability.

Table 2.1: Parameters not estimated

Parameter	Description	Value
σ	Risk aversion	2
β	Discount factor (annualized)	0.9615
r	Interest rate (annualized)	0.04
ρ	Unemployment replacement rate	0.5*
ϕ	Pensions replacement rate	0.44
τ	Marginal tax rate	0.15 $y \leq 1.37$ 0.28 $y > 1.37$
$\delta^h, i = 1$	Rate of depreciation of human capital (annualized)	0
$\delta^h, i = 2, 3$	Rate of depreciation of human capital (annualized)	0.03
n_w	Periods in labor market	38 * 8
n_r	Periods retired	15 * 8

Note: *Per period benefits are subject to an upper limit set to 0.6.

and δ_1), and of the job finding function ($\xi_1, \xi_2 = \xi_3$) are identified from the education specific unemployment rates and the average weeks of unemployment.

Labor market policies As both the UI scheme and the labor income tax policies have important effects on search effort, it is important to have realistic calibrations of the labor market policies. Thus, I will not require that the government runs a balanced budget in the model. I calibrate the tax function to the US tax scheme in place between 1993 to 2001 which covers a large fraction of the periods used for the estimation. The replacement rate of pre-unemployment earnings has been stable at 50 percent throughout the period, but the maximum benefits has changed during the period. I calibrate the maximum benefits per period in the model, using detailed information on maximum benefits by states in the period 1985 to 2000²¹. The upper limit is set based on two measures which I compute for all age and education groups; the fraction of workers for which the upper bound is binding, and the deviation between the implied replacement rate and a 50 percent replacement rate. Based on this I set the maximum benefits equal to half the wage of workers in the group "High School graduates and some College" at age 25. For more information on the calibration of the policy functions, see appendix A. The pension replacement rate is set to 0.44, which is the same values used by [Michelacci and Ruffo \(2011\)](#).²²

All parameter values that are not estimated are summarized in table 2.1.

In the estimation I target the percentage deviation between the targets and the simulated moments. The parameter values obtained from the indirect inference estimation are given in table 2.2. The curvature of the disutility of search effort, which is measured by γ , is comparable to the micro estimates for labor effort, which lies in the range of 0 – 0.5, see e.g.

²¹I am grateful to Raj Chetty for providing the data.

²²The pension replacement rate is taken from data on male workers according to [OECD \(2007\)](#). This is also in line with the findings by [French and Jones \(2012\)](#) that Social security replaces about 40% of pre-retirement earnings.

Table 2.2: Parameter estimates, targeting age 25-60.

	Preferences	Human capital	Job separation/finding		
γ	0.3268	A_2	0.0174	$\delta_{0,1}$	0.0746
b	57.9753	A_3	0.0237	$\delta_{0,2}$	0.0350
		d	0.0326	$\delta_{0,3}$	0.0170
				δ_1	1.3965
				ξ_1	0.0809
				$\xi_{2,3}$	0.4757
<i>SSE</i>	0.4090				

Note: The targets for the estimation are life cycle profiles for real wages, the unemployment rate and unemployment duration. The moments from the model are based on a draw of 10000 individuals. SSE refers to the sum of squared errors.

MaCurdy (1981) and Altonji (1986) for early contributions, and Ham and Reilly (2002) and French (2005) for more recent contributions.²³ The estimate is also similar to, although lower, the estimate presented in chapter 1, which finds $\gamma = 0.47$ for labor effort in a comparable model with human capital, but which disregards unemployment. Production of human capital becomes more difficult with age as d is estimated to be above zero. The job separation rates and job finding rates are discussed below.

The model fit is fairly good for real wages and the unemployment rate and somewhat weaker for the duration of unemployment, see figure 2.2. Taken together the model seems to produce a reasonable fit to the US economy, which makes the quantitative analyses performed below reasonably informative about the trade-offs and welfare costs faced by the government.

The implied job finding rates and job separation rates are shown in figure 2.3. A typical reference is the average job finding rates and the job separation rates found by Shimer (2012). He finds a monthly job separation rate of about 4 percent, and a monthly job finding rate which fluctuate around 30 percent for the sample period considered here. The job separation rates seems to be in line with the finding by Shimer, taking into account that the model period here is 1.5 months, where high educated have a lower job separation probability than the average rate found by Shimer and low educated have a higher separation rate compared to the average. The job finding probability is somewhat lower than what Shimer finds.

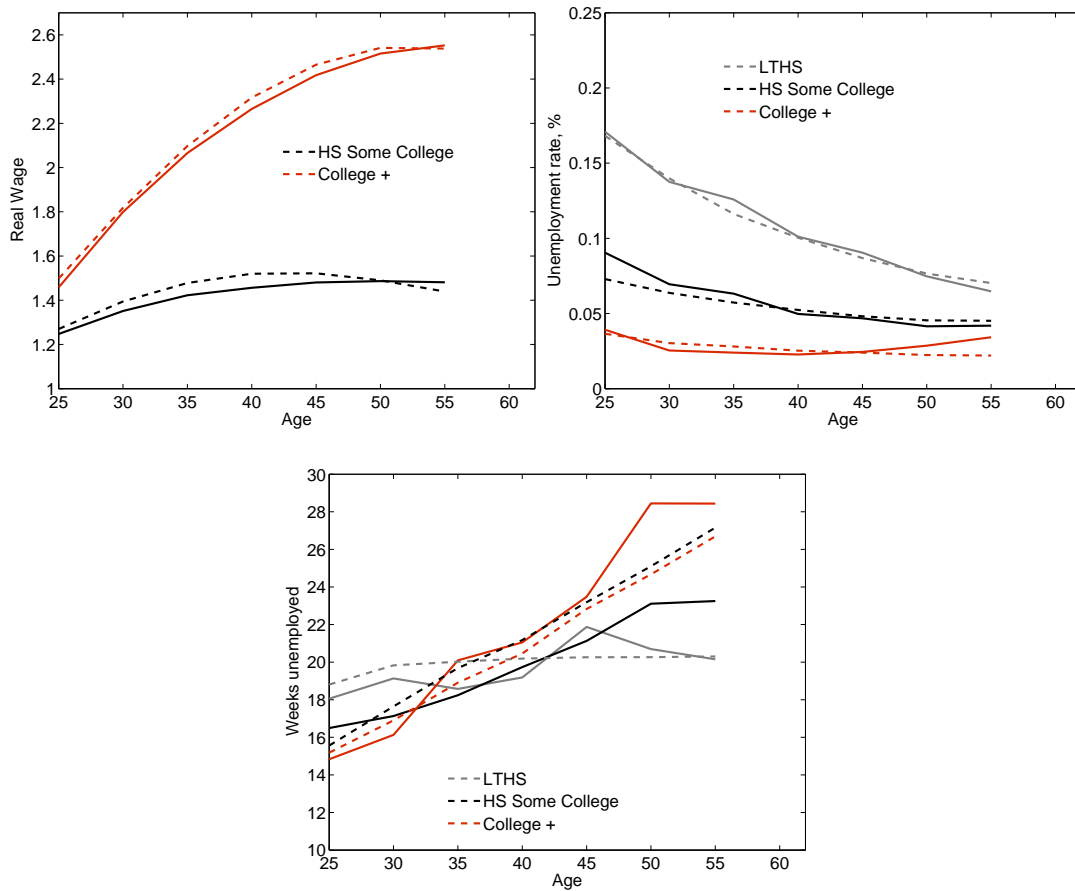
I now turn to the comparison of the search effort in the benchmark model with the search effort in the optimal contract.

2.4 Deviations from the optimal contract

In this section I aim at quantifying the importance of the moral hazard problem of unemployment insurance and the tax distortion problem. As discussed above, one expect the moral hazard problem to be mild among young medium to high educated workers compared to older

²³See Pencavel (1986) for a survey of this literature.

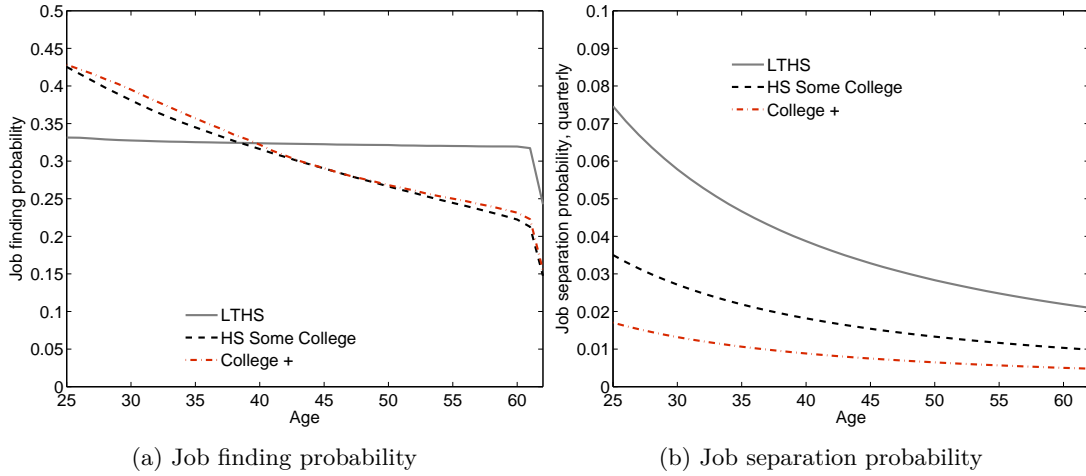
Figure 2.2: Model fit



Note: The solid lines are the data moments whereas the dotted lines are the simulated moments. The moments are 5 year averages, where the data refers to the youngest age, i.e. the value at age 25 refers to the average from age 25 to age 29.

workers as they have a strong incentive to search for a job as they forgo the opportunity to accumulate high return human capital when unemployed. However, the distortionary effects of labor income taxes may be large also for young workers, as it distorts the accumulation of human capital. The tax distortions are simply created by the need to finance the UI, and also other expenses. For the medium and highly educated, the tax distortion problem differs over the life cycle due to varying labor productivity and as the importance of human capital accumulation varies. As older workers are highly productive workers, it is very costly to have them unemployed as they both receive high unemployment benefits and the government forego important tax income which is needed to finance benefits and pensions. And, as older workers are high income workers the more progressive the tax system, the larger is tax distortions as the difference between the private cost of unemployment and the social cost of unemployment increases. For young unemployed workers the main distortion created by taxes is the distortion of human capital accumulation: with positive taxes workers net return to human capital accumulation, which is the relevant measure of the worker, is less than the gross return to human capital accumulation, which is the relevant measure for the social planner. The wedge

Figure 2.3: Job separation and job finding probabilities



Note: Job finding and job separation probabilities implied by the estimated model. The period is 1.5 months.

between the gross and the net return to human capital accumulation obviously widens with higher taxation and/or more progressive taxation.

To quantify the net importance of the moral hazard problem and the tax distortion problem, I compare the search effort in the optimal contract with the search effort in the benchmark economy for different age and education groups. Using the fact that the tax distortions are zero if taxes are zero, I measure the relative importance of the moral hazard problem and the tax distortion problem by comparing the deviation from optimal search effort in a model with and without labor income taxes. Note that the measure of the moral hazard problem is a relative measure, and only takes into account the "excess" moral hazard problem relative to the optimal contract. However, under the reasonable assumption of unobservable search effort, the optimal contract is a natural benchmark.

2.4.1 The optimal contract

I simulate the optimal contract for each education group separately. The expected total (discounted) cost of the contract offered by the planner to a specific education group is set equal to the (discounted) expected net cost of the government in the benchmark economy plus the initial assets of the workers. The initial assets are included as I assume that in the optimal contract the planner would fully tax any initial assets. The expected net cost in the benchmark economy, \tilde{c} , is given by the expected tax income minus the expected unemployment benefits and the expected pensions, all discounted to the first period, plus initial assets:

$$\tilde{c} = - \sum_{j=1}^{n_w} \beta^{j-1} E_{t=1} \{ \tau(h_j) \} + \sum_{j=1}^{n_w} \beta^{j-1} E_{t=1} \{ b(h_j) \} + \sum_{j=n_w+1}^{n_r} \beta^{j-n_w-1} E_{t=1} \{ \tau(\pi h_{t_w}) \} + k_0. \quad (2.42)$$

The total net costs are not restricted to be zero for each education group for two reasons;

First, as the total level of income taxes, and its progressivity, matters for the wedge between the private return and the social return to human capital accumulation, it is important to have a realistic tax function in the benchmark model. Second, I want to include some implicit redistribution between education groups, where highly educated workers run a larger life-time budget surplus compared to low educated. For simplicity, I assume that any budget surplus is simply thrown away and do not provide any utility.

The promised life-time utility for a worker with education level i , $v_{s,i}$, is found by solving the following equation

$$C^s(1, h_{1,i}, v_{s,i}) = \tilde{c}. \quad (2.43)$$

Note that when I compare the model with and without taxes, I also adjust the optimal contract according to the net budget associated with each case. For the other labor market policies I analyze, I simply adjust the tax rates to ensure that the government runs the same education specific deficit/surplus as the benchmark model with progressive taxation.

2.4.2 The benchmark economy relative to the optimal contract

The next step is to compare the search effort in the benchmark model with the search effort in the optimal contract. And, measure the relative importance of the moral hazard problem and the tax distortion problem. I pursue in two steps: First, I simulate the two models with the same initial conditions and compare each workers search effort in the two models.²⁴ I assume the following initial conditions: all workers are initially unemployed, have an initial education specific human capital as specified in section 3, and have asset holding equal to one month of labor income.²⁵ Second, to assess the importance of the moral hazard problem and the tax distortion problem I simulate the models assuming that there are no income taxes, as tax distortions are zero if taxes are zero. By comparing the deviation from optimal search effort with and without taxes, I measure the severeness of the moral hazard problem versus the tax distortion problem. One could also solve the model with non-distortionary taxes rather than assuming that there are no taxes. However, it is nontrivial to solve for a set of non-distortionary taxes; any tax which affects the utility of consumption for unemployed and employed differently will distort search effort. This is easily seen from the first order condition with respect to search effort:

$$g'(e_t) = \beta \pi'(e_t, a_t) [V_{t+1}^e(\cdot) - V_{t+1}^u(\cdot)],$$

²⁴In order to not measure the deviation of search effort due to previous deviations, I assume that the job finding rate until age t in the benchmark model is given by the optimal contract, so that the accumulation of human capital (an assets) are the same in both models. I then compare search effort at time t .

²⁵The initial asset holdings are set to minimize the distortions of search effort due to lack of assets to smooth consumption at young ages. Although this is indeed an important distortion, as discussed by e.g. [Chetty \(2008\)](#), it is not the focus of the paper and complicates the discussion of the relative importance between the moral hazard problem and the tax distortion problem.

which shows that for a tax to be non-distortionary it cannot affect the difference between the future value of being employed, $V_{t+1}^e(\cdot)$, and the future value of being unemployed, $V_{t+1}^u(\cdot)$. Thus, as consumption differs across the two states, and this difference varies with age and education, taxes need to account for all these differences in order to be non-distortionary. Therefore, I limit the analysis to the case of no taxes. Note that there will still be taxes in the optimal contract, as the possibility of optimally setting reemployment taxes improves welfare in the constrained best, see e.g. [Hopenhayn and Nicolini \(1997\)](#).²⁶ As emphasized above, the moral hazard problem in the benchmark model is then measured relative to the moral hazard problem in the optimal contract, and is a measure of excess moral hazard.

In this section I set as benchmark an unemployment policy with 50 percent replacement rate irrespective of the workers income level, to enhance comparison across groups. The case with a maximum per period benefit, as assumed above, is studied below. The benchmark labor income tax is however as specified above, and features a degree of progressivity which is calibrated to match the US policy.

The deviations from optimal search effort over the life cycle for the three education groups are shown in figure 2.4. There are two main findings obtained from the two figures; First, the deviation from optimal search effort across age and education is inversely related to the return to human capital accumulation; whereas the return to human capital accumulation decreases with age and increases with education, the deviation from optimal search effort increases with age and decreases with education. For the benchmark policy, the deviation is on average 21 percent, 11.5 percent and 9.9 percent over the life cycle for workers with 'LTHS', 'HS-Some college' and 'College +', respectively. Moreover, the deviation from the optimal contract is increasing over the life cycle for the two highest education groups, and is about constant over the life cycle for the low educated. The increase is due to both an increase in the moral hazard problem and in the tax distortion problem.

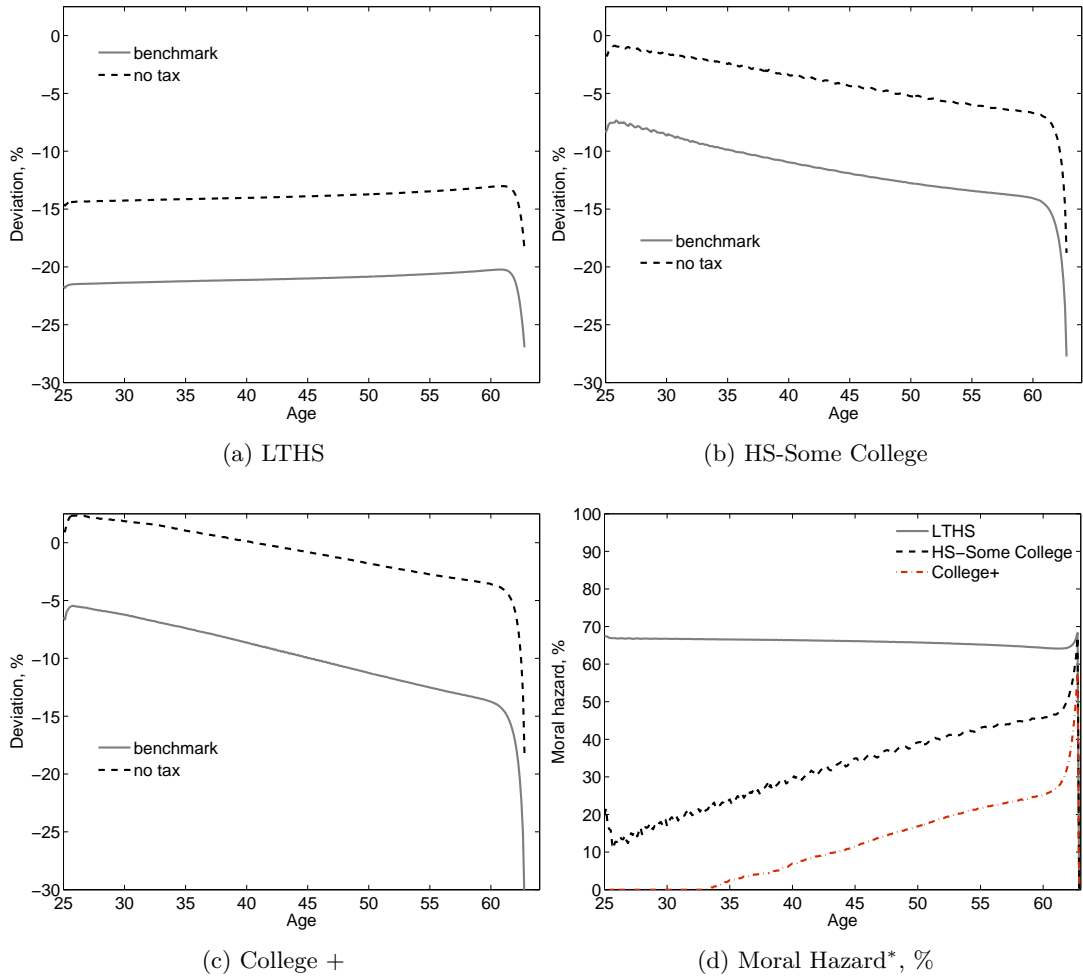
Second, by comparing the deviation with and without taxes one can assess the relative importance of the moral hazard problem versus the tax distortion problem. The deviations from the optimal contract is considerably smaller when only including the moral hazard problem. For young workers with medium and high education, the moral hazard problem is indeed very small and for high educated workers the precautionary motive seems to makes workers exert more effort than the optimal contract. However, to conclude that social costs of generous UI benefits to young workers are modest, based only on the modest moral hazard costs, would lead policy makers to considerably underestimate the true costs. For young workers with high education the moral hazard problem accounts for virtually none of the total deviation and it increases to about 25 percent for older workers, see lower right panel of figure 2.4.²⁷ For workers with medium education the moral hazard problem accounts for 10 – 20

²⁶The reemployment tax is however less efficient than in [Hopenhayn and Nicolini \(1997\)](#), as argued by [Sopraseduth et al. \(2007\)](#). The reason is due to the short tax horizon in a life cycle model compared to an infinite horizon model. This is particularly true for older workers.

²⁷To ensure a meaningful comparison for workers with a College degree, the deviation from optimal effort is reduced by a fixed amount to ensure that the deviation is never positive. However, the importance of moral hazard is actually negative in this region. But due to values very close to zero in the denominator, the negative

percent for young workers and increases to close to 50 percent for older workers. For workers with low education and a flat wage profile, both the tax distortion problem and the moral hazard problem are constant over the life cycle, and the moral hazard problem dominates the costs by accounting for close to 70 percent of the social costs of unemployment benefits to this group.

Figure 2.4: Deviation from the search effort in the optimal contract by education groups, in percent



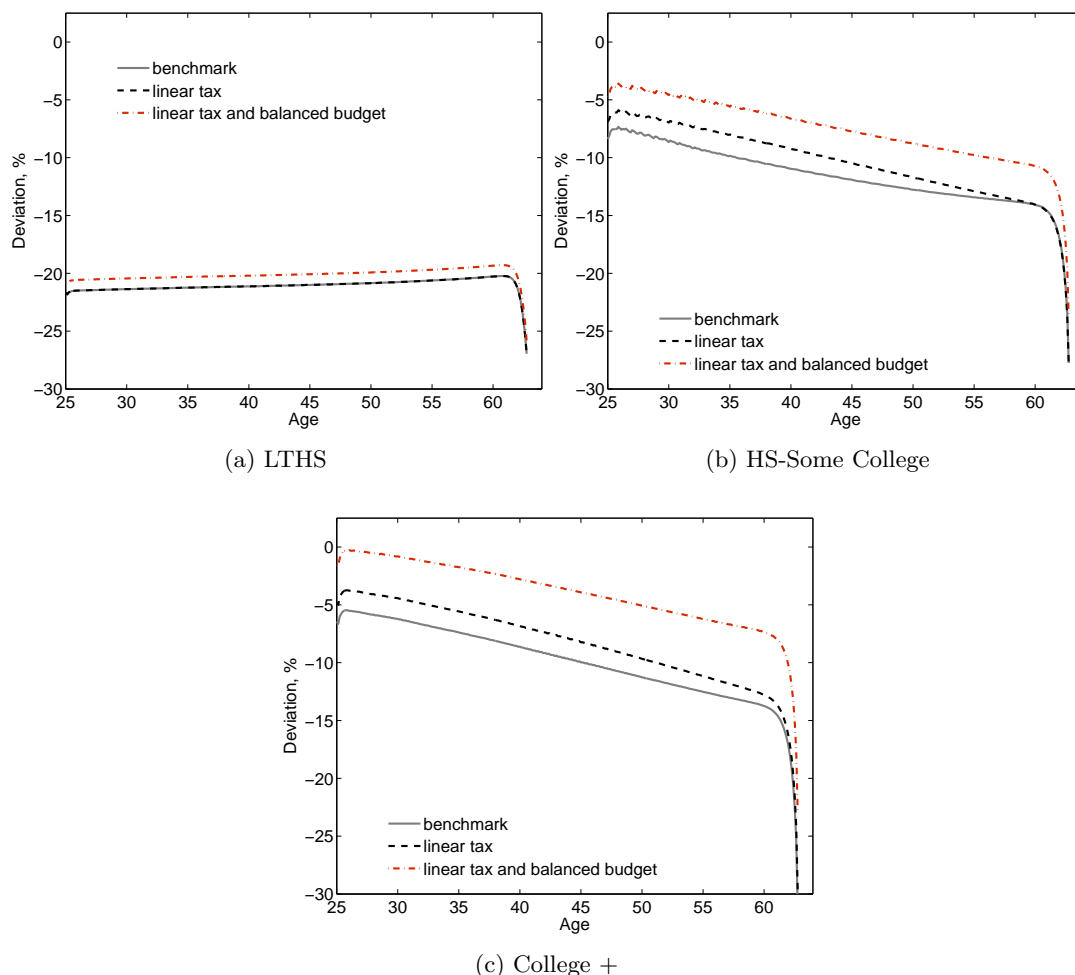
Note: The lines refers to different tax policies in the model, where the benchmark is the progressive tax scheme.

*For college graduates, the relative importance of moral hazard has been modified to address the positive deviation with zero taxes. For more information see the text.

In the analysis above, the labor income tax was progressive and the government did not run a balanced budget, neither for each education group nor for the economy as a whole. This was motivated by the fact that labor income taxes in the US are progressive, and they are used to finance more than just pensions and unemployment benefits. However, in the importance of moral hazard becomes very large. However, this will unfortunately yield a value of zero moral hazard costs for the year with the maximum positive deviation in the economy with no taxes.

literature it is common to perform the same analysis assuming that the government runs a balanced budget and that taxes are linear. When comparing a progressive and linear tax, I adjust the linear tax so that they generate the same net tax revenues as the progressive tax. When assuming that the government runs a balanced budget per education group the linear tax is adjusted accordingly. For the low educated this does not matter much as they face linear taxes under the benchmark tax policy and almost runs a balanced budget, see upper left panel of figure 2.5. For the medium and high educated the deviation from optimal search effort decreases substantially with respect to the benchmark case; when workers face a linear tax and the government runs a balanced budget the average deviation falls from 11.5 to 7.5 percent for 'HS-Some College', and from 9.9 to 4 percent for College graduates. Moreover, among young workers with a College degree the deviation is close to zero. Thus, both the assumption of a linear tax and a balanced budget substantially reduces the deviation from the optimal search effort.

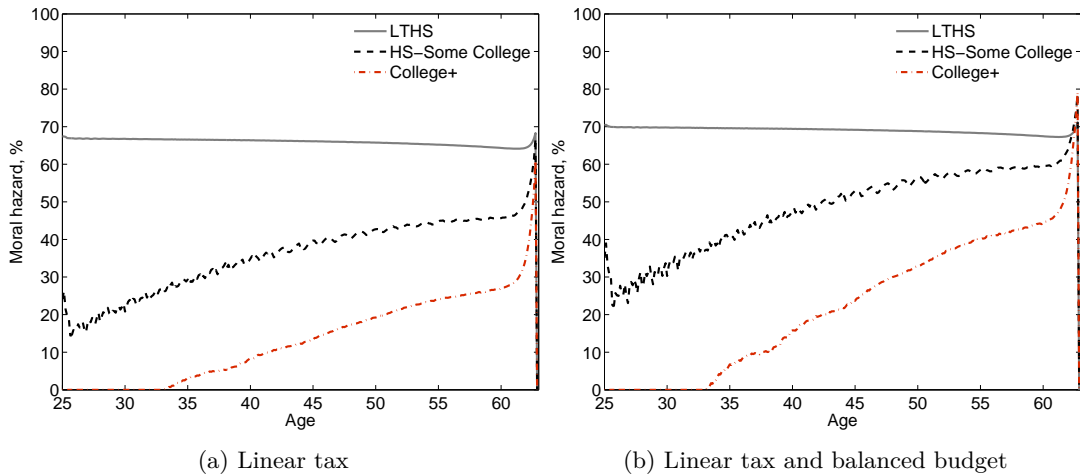
Figure 2.5: The effects of a linear tax and a balanced budget on the deviation from optimal search effort, in percent



The importance of moral hazard in the cases with a linear tax and a balanced budget is

somewhat higher for the two top education groups, whereas it is almost unchanged for the low educated, see figure 2.6. However, it is still the case that the main social costs associated with unemployment insurance is not the moral hazard problem but distortions created by labor income taxes needed to finance the UI. Thus, even the taxes needed to finance only the unemployment benefits induces tax distortions which are so large that they account for most of the social costs of UI provision for the two highest education groups.

Figure 2.6: The importance of moral hazard*, in percent

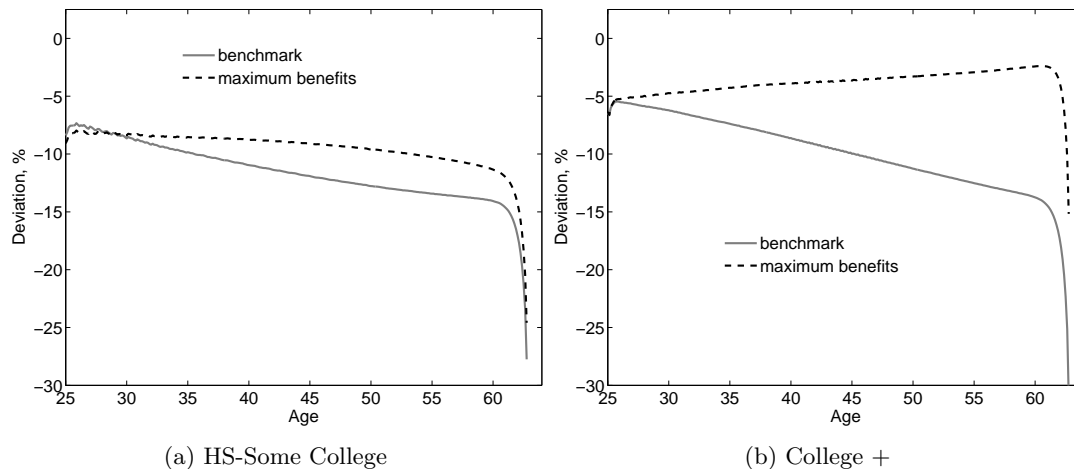


*For college graduates, the relative importance of moral hazard has been modified to address the positive deviation with zero taxes. For more information see the text.

Finally, I consider the case where unemployment benefits are subject to a cap, that is, for income above a given threshold the replacement rate is regressive. In the calibration above the maximum level is set so that it starts binding at age 25 for the two highest education groups, but never binds for the low educated. For the middle education group the replacement rate decreases from 50 percent for young workers to 40 percent for older workers, whereas for the high educated it decreases from about 45 percent for young to 25 percent for older workers. Regressive benefits decreases the deviation from optimal search effort for older workers, as they face a less generous UI system, see figure 2.7. For College graduates the search incentives created by the regressive benefits are so strong that the deviation from the optimal search effort becomes decreasing in age, and is very close to the optimal level for old workers.

The welfare gains, measured in consumption equivalents, $W1$, of implementing the optimal contract differs substantially between education groups, see table 2.3. The low educated has the highest welfare gains of implementing the optimal contract, corresponding to about one percent increase in consumption. However, for the two highest education groups the welfare gains are modest, corresponding to a roughly a 1/3 of a percent increase in consumption for the medium educated and close to 1/5 of a percent increase for the high educated. The welfare gains are considerably smaller than what e.g. Michelacci and Ruffo (2011) find. But, this is as expected as they assume a tight borrowing constraint which limits the workers ability to optimally smooth consumption over the life cycle.

Figure 2.7: Effects of regressive benefits on the deviation from the optimal search effort, in percent



The welfare gains are modest, as lower search effort in the benchmark models yields sizable welfare gains compared to the optimal contract. The consumption increase needed to equalize the life time utility of consumption, $W2$, however, is substantially larger. For the model with labor market policies closest to the US, which has progressive taxes and a maximum limit, the consumption gains needed to equalize the life time utility of consumption are at 2.81 percent, 1.2 percent and 0.58 percent for workers with low, medium and high education, respectively.

Table 2.3: Welfare losses

		LTHS	HS-Some College	College+
Benchmark	$W1$	1.08	0.34	0.18
	$W2$	(2.81)	(1.28)	(0.78)
Linear tax	$W1$	1.08	0.36	0.22
	$W2$	(2.81)	(1.13)	(0.62)
Maximum benefits	$W1$	1.08	0.34	0.17
	$W2$	(2.81)	(1.20)	(0.58)

Note: $W1$ refers to the consumption gain needed to equalize life time utility with the optimal contract. $W2$ refers to the consumption gain needed to equalize the life time utility of consumption only.

This section offers some key lessons when assessing the deviations from optimal search effort. First, there is a significant degree of heterogeneity across age and education groups due to different returns to human capital accumulation. Second, social costs associated with moral hazard problems are not the main problem with unemployment insurance, rather, it is

the tax distortion problem caused by the need to finance the UI through labor income taxes that accounts from the main costs of unemployment insurance. Third, it is important to consider the total tax burden of employed workers when one wants to assess the deviation between the search effort exerted and the optimal level. And, finally, assumptions about labor market policies matters. Both the degree of progressivity in taxes and the regressivity of benefits (due to maximum per period benefits) affects the search effort of workers and the deviation from the optimal contract; More progressive taxes increases the deviation whereas more regressive benefits decreases the deviation.

2.5 The optimal contract

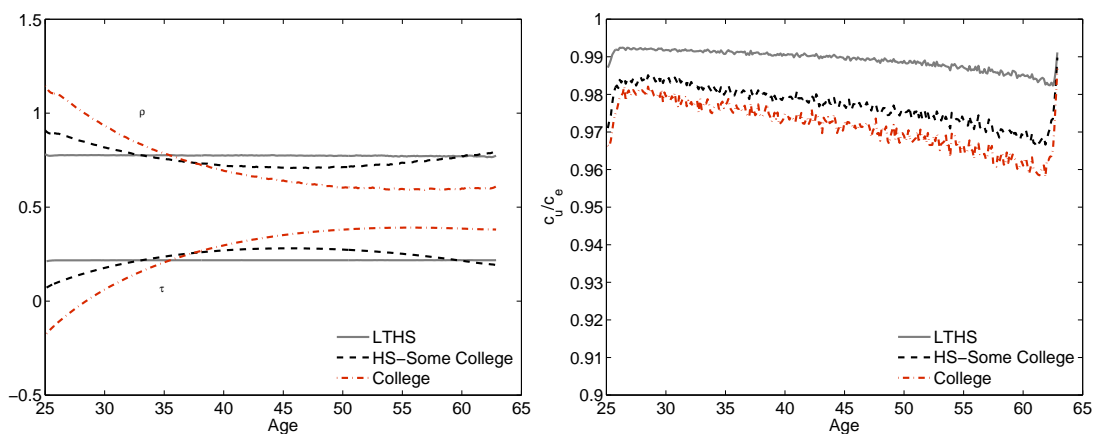
As shown above, search effort is substantially below what the optimal contract would require, but the degree to which search effort deviates varies between age and education groups. In this section I discuss the optimal contracts given to each education group in some more detail. In particular, I focus on the differences across age and education groups, which is due to different returns to human capital accumulation. However, I will leave a discussion of possible decentralizations to future research.

The average tax rate and replacement rate over the life cycle for the three education groups are shown in figure 2.8. Whereas the age-average of the tax rate and the replacement rate are constant over the life cycle for workers with education less than High School, replacement rates decreases with age and tax rates increases with age for the College graduates. The middle education group has more of a hump-shape on both tax rates and replacement rates. The net replacement rate however, which is benefits over income net of taxes, $\frac{B}{h-T}$, is highest for the low educated and decreasing in education and in age. This reflects the need to provide workers with a strong career effect with sufficient incentives to search for a job to accumulate high return human capital.

The profiles for tax rates and the gross replacement rate for College graduates are similar to the ones found in [Michelacci and Ruffo \(2011\)](#). They found that implementing age-dependent taxes and benefits, where replacement rates decrease with age and tax rates increase, would yield significant welfare improvements in the US. The results obtained here indicates that such a labor market policy may not be optimal for the lowest education groups. Moreover, the educational differences in the optimal taxes and transfers indicate that policies which do not take educational differences in the return to human capital accumulation into account may be quite inefficient.

Figure 2.9 shows how the optimal contract changes with unemployment duration for 4 age groups. For all age and education groups the replacement rate falls with duration and the re-employment tax increases with duration, see the first and second row. The fall in replacement rates and the increase in tax rates are larger for higher educated workers. For the two highest education groups the magnitude of the fall in replacement rates and the increase in tax rates over the duration both declines with age, whereas the opposite is true for the low educated. For all education groups the utility gain of finding a job increases with age and

Figure 2.8: Policies in the optimal contract, age and education averages

(a) Tax rate ($\rho = B/H$) and the gross replacement rate ($\tau = T/H$)

(b) Consumption replacement rate

with duration, see the last row. However, as discussed above, the higher is the job finding rate the more is the utility gain driven by punishment and the lower is the job finding rate the more important is reward.

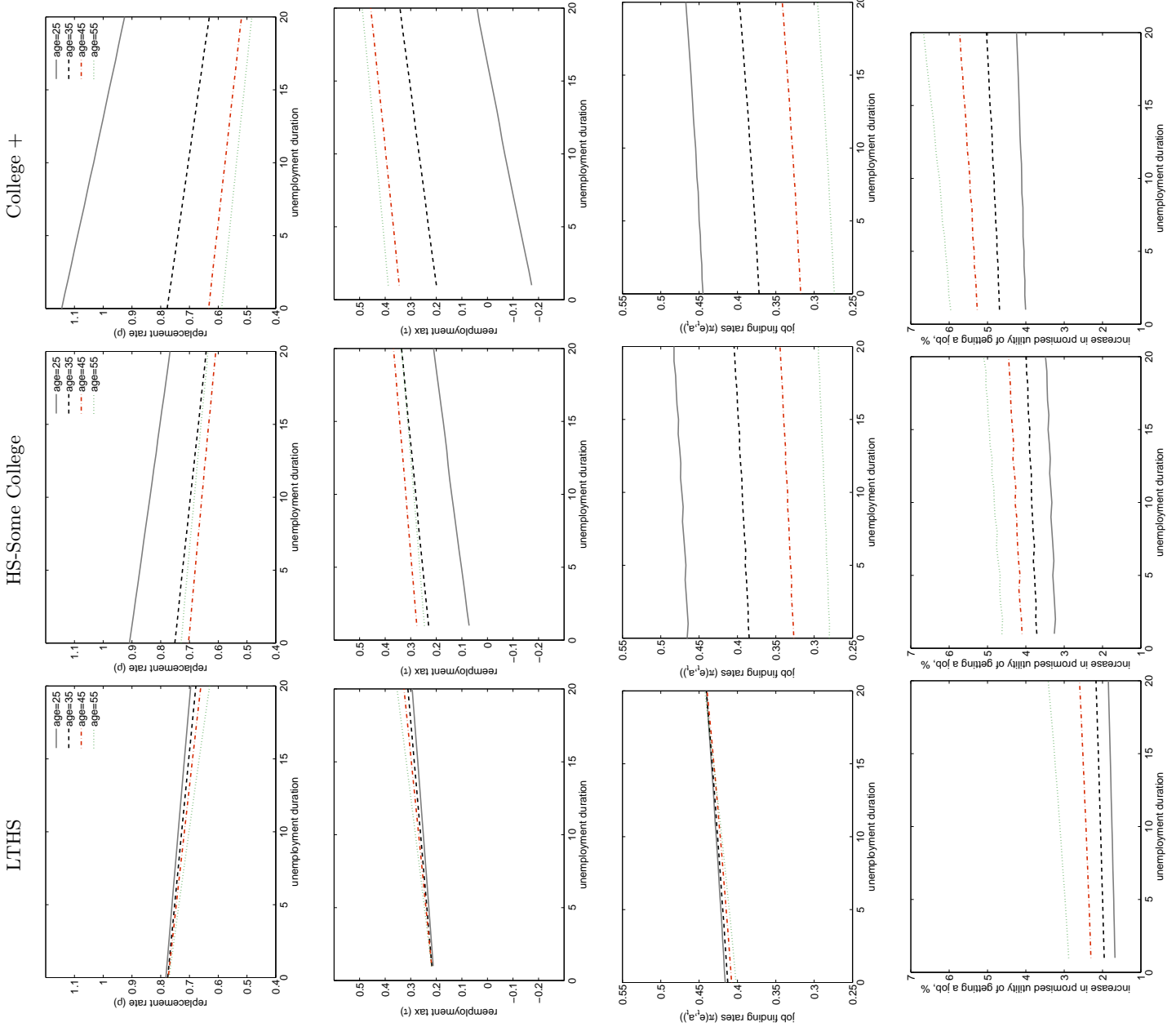
The optimal contracts show a lot of similarities across education groups, but there are also some important differences. Any implementation of the optimal contract need to take these educational differences into account.

2.6 Conclusion

In this paper I show that it is important to take into account heterogeneous returns to human capital accumulation when analyzing both the degree to which search effort deviates from the socially optimal level, and the reason behind the deviation. In particular, I analyze the effects of heterogeneous returns to human capital on the moral hazard problem of unemployed workers and on the distortionary effects of labor income taxes. Under the assumption that the government do not have access to lump-sum taxation, labor income taxes distorts search effort by lowering after-tax re-employment wages, but importantly, taxes also lowers the return to human capital accumulation. The latter is important as contemporaneous distortions of search effort has long lasting effects on future productivity and wages through both a larger depreciation and reduced accumulation of human capital.

To analyze the importance of both the moral hazard problem and the tax distortion problem, I develop a life cycle model featuring heterogeneous human capital accumulation across age and education, and costly search effort. I estimate the model using indirect inference methods, and match the model to the US economy both in terms of key variables and labor market policies. By comparing the search effort exerted in the estimated model with the effort specified in an optimal contract offered by the government who do not observe the search effort exerted, I obtain a measure of the deviation of search effort from the (constrained)

Figure 2.9: The optimal contract



optimal level. Moreover, as the tax distortion problem is due to positive taxation, I isolate the importance of (excess) moral hazard by comparing the optimal contract with the search effort exerted by workers who face zero income taxes.

The three main findings of this paper are: (i) the main social costs associated with today's US unemployment insurance are not due to moral hazard problems, but are due to the distortionary effects of labor income taxes needed to finance the insurance. For young workers the moral hazard problem accounts for less than 20 percent for workers with High School and some College, and close to zero percent for College graduates. For older workers, the moral hazard problem accounts for about 25 percent and 45-50 percent for workers with High School and some College and College graduates, respectively. For workers with less than High School, the moral hazard problem is constant at 70 percent.

(ii) The magnitude of the *moral hazard problem* and the *tax distortion problem*, differs substantially over the life cycle and across education groups. I find that the deviation of search effort is negatively related to the return to human capital accumulation. That is, the deviation is increasing in age and decreasing in education. And, (iii) the degree of tax progressiveness and benefit regressiveness has important effects on the deviation of search effort from the optimal level. More progressive taxes increases the deviation from optimal search effort, and more so for young workers. The effect of progressive taxes are more important for younger workers as more progressive taxes reduces the returns to human capital accumulation. More regressive benefits, through e.g. lower maximum benefits, has the opposite effect: more progressive benefits decreases the deviation from optimal search effort, and more so for older workers. The effect of regressive benefits are strongest for older workers as they have higher wages and thus obtain lower effective replacement rates.

Finally, I also show that the optimal contract offered to each education group differs in an important way: whereas the average replacement rate is falling with age and the average tax rate is increasing in age for the two highest education groups, the average replacement rate and tax rate is constant across age for the low educated group. This reflects the wage patterns of the education groups and the consumption smoothing motive of the planner. Although I do not make any attempt on proposing a set of policies which could bring the US welfare closer to the constrained best, I do believe that such a policy need to take both age and educational differences into account.

Appendix

A Moments

The targets for the indirect inference estimation are created using monthly CPS data from 1979 to 2008 on real wages, unemployment rates and the duration of unemployment.^{28,29} I choose to end the sample in 2008 to avoid the recent financial crisis to influence the later part of the life cycle measure. I use data on worker between 25 and 60 years with a well defined entries for labor force participation and education level. I exclude the following set of workers (the data codes are in parentheses): self employed (selfemp=1), workers with positive business income (selfinc=1), students (student=1 and studpt==1), worker who work less than 35 hours due to illness (why3594=5 and why2579=10), and employed workers with zero income (rw=0 & empl=1).

B Labor market policies

The tax function and the UI policy are calibrated to match the US system in the estimation period, 1979-2008, as well as possible. The tax function is calibrated using the tax scheme in place from 1994 to 2000 (OBRA93). For average to lower income earner, the OBRA93 tax scheme match well already from 1987, with a stable income tax at 15% for the first tax bracket.

When calibrating the tax function to match labor income levels in the model, I use annual income data from CPS³⁰ in the year 2000 and the tax ranges for year 2000. As the changes in income-ranges for the tax brackets are only adjusted for inflation between 1994-2000, the benchmark-year should not matter. I use the income-ranges for the "head of household" specification, and compute the average labor income tax rate paid by all age-education groups in year 2000. I then choose the tax ranges in the model which provides the best fit between the average labor income tax in the year 2000 data and the average tax rate paid by the workers with an income equal to the estimation targets specified above. The resulting marginal tax function, shown for the relevant income levels, is

$$tax_t = \begin{array}{ll} 0.15 & \text{if } y < 1.37 \\ 0.28 & \text{if } 1.37 \leq y \leq 3.5 \end{array} ,$$

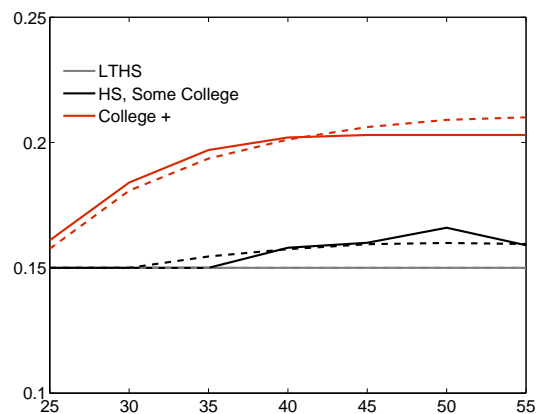
where y is the labor income. The average tax rate in the data and in the model is shown in figure B.1. This also match very well the marginal income tax rate for the highest and lowest education groups, which in the period from 1987 to 2008 had a marginal tax rate of 15% and 28%, respectively.³¹

²⁸The data are from CEPR, Center for Economic and Policy Research. 2006. CPS ORG Uniform Extracts, Version 1.5 . Washington, DC

²⁹The data on unemployment duration is only available from 1994.

³⁰Data from: Miriam King, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick. Integrated Public Use Microdata Series, Current Population

Figure B.1: The calibrated tax rate and US tax rates in year 2000



Note: Solid lines is the average tax rate for the year 2000 using CPS data on income and the official tax brackets. The dotted lines are the calibrated average tax rate paid by workers with an income equal to the sample average of income, which is the calibration target used for the model computed from CPS data.

The UI policy is a two parameter function specifying the replacement rate and an upper bound on per period benefits. The replacement rate is set to 0.5, which is common in the literature, see e.g. [Chetty \(2008\)](#). To calibrate the upper bound on benefits I use maximum weekly benefits by states from the Survey of Income and Program Participation (SIPP) over the period 1985 to 2000.³², and individual data on weekly income from the CPS in the same period. Using state specific benefit levels, I take into account differences in state level wages which may be important. Contrary to above, I include all cohorts in the sample to obtain information on all ages. However, the restriction on the sample apart from the cohort restrictions are the same as above.

I set the upper limit on benefits based on two measure: the share of workers where the upper limit on benefits is binding, that is if weekly income exceeds two times the maximum weekly benefits. And, the mean income relative to twice the maximum benefits. Both measures are computed for all ages and three education levels. The two measures are shown in figure B.2. For workers with less than High School, the share of workers with a binding benefit restriction is maximum 40 percent, and the average income is below the maximum benefit for all ages. For workers with a High School degree and some College, the share of workers with a binding restriction is above 50 percent from the age 28 an onwards, and the average income is above the maximum benefits for the same age interval. For College graduates, the share of workers with a binding restriction is close to 100 percent for most ages, and the average income is always above the maximum benefits. Based on this, I set the upper limit on the benefits equal to 50 percent of the income level for workers with a High School degree at age 25. Thus, for the two highest education groups the upper limit on benefits will be binding for

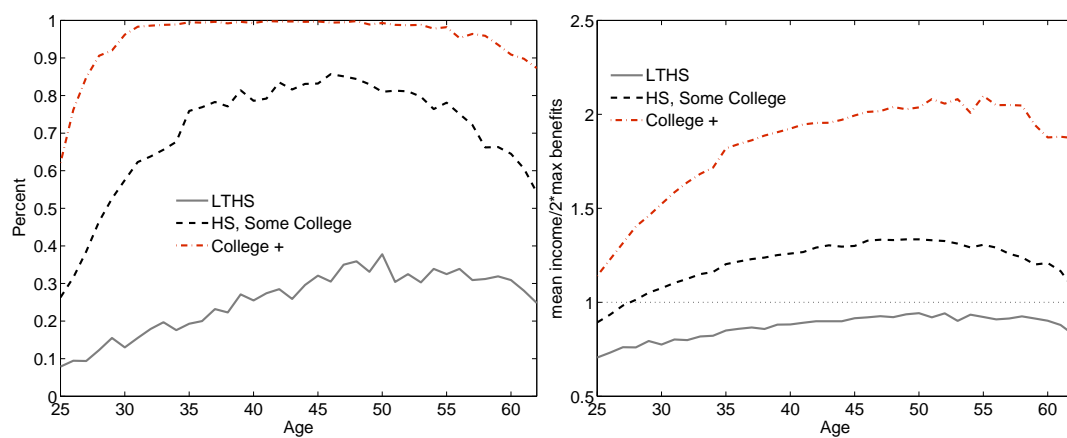
Survey: Version 3.0., Minneapolis: University of Minnesota, 2010.

³¹I compute the marginal tax rate as the marginal rate paid on the last dollar of the annual labor earning, not taking any transfers into account. More specifically, the marginal tax rate is obtained using the Stata built-in command `egen mtr`.

³²I thank Raj Chetty for making the dataset and STATA codes available.

all ages, whereas it will never be binding for the low educated.

Figure B.2: Share of workers for which the upper limit on benefits are binding, and mean income relative to the maximum benefits



(a) Share of workers with a binding benefit restriction.
 (b) Average income relative to 2 times the maximum weekly benefits.

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3 Household Risk, Labor Supply and Precautionary Wealth Accumulation

3.1 Introduction

When it comes to income fluctuations and employment risk the individual relies to a large extent on labor supply and precautionary savings for insurance. The main reasons are that private insurance markets do not exist, that individuals are credit constrained, and that the insurance coverage provided by governments in case of loss of employment is limited.¹ Another potential source of income insurance is the marriage itself through income pooling and spousal labor supply. [Lundberg \(1985\)](#) investigated the insurance potential of the latter channel in what she called the "added worker effect", but spousal labor supply as income insurance has been neglected in the literature on income risk and savings until recently.² [Blundell et al. \(2012\)](#) and [Ortigueira and Siassi \(2013\)](#) are two contributions highlighting the potential importance of intra-household risk-sharing through spousal labor supply.

This paper takes a first step towards a better understanding of the nature of income risk that different households face by studying the relation between co-movement of income shocks and precautionary asset holdings. In particular, we want to assess whether households perceive spousal labor supply as a source of income insurance, and how this insurance mechanism vary with the co-movement of income shocks. The idea is that if there is income pooling within the household and labor supply is inelastic, all that matters for the precautionary savings is the variance of total income.³ However, if households perceive spousal labor supply as a source of insurance, it is evident that this mechanism should work better the lower the

This chapter is joint work with Andreas Fagereng and Maria Gustafsson. The chapter has benefitted from discussions and useful suggestions from Christopher Carroll. I thank Statistics Norway for their hospitality during the work on this project.

¹Unemployment insurance does not cover 100 percent of the income and there is usually a ceiling. Evidence on credit constrained households is provided by, for example, [Jappelli et al. \(1998\)](#), and by [Crossley and Low \(2012\)](#) for job losers in particular.

²The initial literature on the added worker effect focused on changes in labor supply along the extensive margin, see e.g. [Lundberg \(1985\)](#). The focus of this paper is on changes in labor supply along the intensive margin. However, we choose to label this effect the added worker-effect, as more recent literature has also used this terminology regarding the intensive margin, see e.g. [Blundell et al. \(2012\)](#).

³Note that the analysis only hinges on the assumption of a minimum of income pooling. That is, that the households share a strictly positive fraction of their labor income.

co-movement in shocks to the spousal incomes. Thus, if the household is using labor supply to smooth shocks we should see that the correlation of shocks to the spouses' wages matters for precautionary wealth accumulation independent of the variance. This prediction can be tested empirically and in order to do so we use administrative data from Norway, which provides detailed information on household income, financial wealth and a rich set of control variables while minimizing the risk of measurement error.

To assess the importance of household insurance through spousal labor supply, we proceed in two steps. First, we first estimate the variance and the correlation of shocks to the income of individuals within a household. The variance and correlation of household income shocks are obtained by removing predictable changes in income and computing the variance and correlation of the residuals. More specifically, we use a rolling windows approach to estimate the parameters, which allows for the variance and the correlation to vary over time for a given household. We find that households in which both spouses have the same education level or are working in the same industry have a higher correlation of income shocks than couples who have different education levels and work in different industries. This is also what we would expect if assortative matching on education and industry could matter for the co-movement of shocks.

Second, we test whether households with stronger co-movement of income shocks, for a given variance, holds larger precautionary buffers. In particular, we regress different specifications of financial wealth on the variance and correlation of income shocks as well as on other relevant household characteristics. In the analysis we attempt to deal with measurement error in the variance and correlation estimates by using the variance in different industry combinations of the individuals in a household over time as instruments. In addition, we also attempt to control for time-invariant, unobserved differences between the households that might bias the coefficient estimates, using the fixed effects estimator. This is possible since we have obtained several estimates of the variance and the correlation for each household. The empirical results strongly indicate that intra-household insurance through labor supply is important. Our preferred estimator - the instrumental variables-fixed effects estimator - indicates that the correlation of income shocks has an important positive effect on the precautionary savings of the household, independent of the variance of total income. More specifically, we find that an increase from the lowest to the highest correlation documented in our sample would predict a median increase in financial assets of 97,144 NOK, or equivalently 16 percent of average yearly disposable income.

In our study the precautionary motive for saving is an important point of departure for the analysis. By now there are several empirical studies testing the strength of the precautionary motive by relating measures of income uncertainty to savings and asset holdings. Of these, several studies find that there is a positive relation between income risk and wealth, although the importance of the precautionary motive varies between studies.^{4, 5} Our analysis shows

⁴See e.g. Guiso et al. (1992); Carroll and Samwick (1997); Kazarosian (1997); Lusardi (1998); Carroll et al. (2003); Alan (2006); and Hurst et al. (2006)

⁵See Browning and Lusardi (1996) for a review of the earlier literature on savings choices and Meghir and Pistaferri (2011) for a summary of the more recent literature.

evidence in favor of the precautionary savings hypothesis as our measure of income variance has a strong positive effect on asset holdings. There are few studies investigating the insurance provided through individual labor supply, and even fewer studies considering the insurance provided by family members. [Kotlikoff and Spivak \(1981\)](#) is one of the first studies to look at insurance through family members, but they do not consider labor income. [Attanasio et al. \(2005\)](#) model a two-person household to investigate the response of female labor force participation to idiosyncratic risks within the family while male participation is exogenous. In an attempt to study the welfare implications of a changing U.S. wage structure, [Heathcote et al. \(2010\)](#) use a model in which both female and male labor supply is endogenous. [Ortigueira and Siassi \(2013\)](#) attempt to quantify the importance of intra-household risk-sharing, calibrating a model with endogenous labor supply of both spouses. Their findings indicate that this risk-sharing is important, especially for households with little wealth. [Blundell et al. \(2012\)](#) find that, when they add family labor supply to assets and taxes, there is little evidence of any other insurance.

Empirical tests of the importance of spousal labor supply for income insurance have focused on the extensive margin. In particular these studies look at whether married women tend to enter the labor market in response to unemployment of their husband and find small, positive effects (see e.g. [Lundberg \(1985\)](#), [Cullen and Gruber \(2000\)](#), and [Juhn and Potter \(2007\)](#)). [Boca et al. \(2000\)](#) do not find that the likelihood of wife employment increases with unemployment of the husband on average. However, in households where wife employment is likely to be "more accepted" they do find a positive effect. [Stephens \(2002\)](#) investigates the response of wives' work effort, including adjustments on the intensive margin. They find small increases in wives' labor supply prior to displacement and larger responses post displacement. Indirect evidence of the importance of spousal labor supply is provided by [Browning and Crossley \(2001\)](#) who find that the expenditure response to an increase in the replacement rate of unemployment insurance is higher for individuals whose spouse was not employed, indicating that spousal income is important for consumption smoothing during an unemployment spell. Similarly, findings by [Lusardi \(1998\)](#) indicate that the precautionary savings motive seems stronger for households with only one earner. On their part, [Juhn and Potter \(2007\)](#) argue that the value of marriage as insurance is likely to have decreased over time due to increased female labor force participation and a more positive co-movement of spouses' employment.

This paper contributes to the literature on insurance through spousal labor supply by considering whether households provide insurance along the intensive margin. The answer to this question has important policy implications. In a companion paper to this [Fagereng et al. \(2014\)](#) we show that the ability of using this channel most likely vary in the population. If spousal labor supply is an important insurance channel for households, but the ability of using it differs among households, it means that some households are to a larger extent exposed non-insurable labor market risk than others. If this risk differs between education and income groups, for example, the policy implications could be different depending on what part of the economy that is hit by an income shock. Furthermore, that households face different

insurance possibilities due to different degrees of income correlation could be important to take into account when evaluating the effect of progressive income taxation and unemployment insurance. Moreover, if labor supply does provide insurance against shocks to labor income, we face the important question of to what extent unemployment insurance may crowd out labor supply, as emphasized by Cullen and Gruber (2000), Engen and Gruber (2001), and Ortigueira and Siassi (2013).

Finally, the findings of this paper points the importance of intra-household risk-sharing through labor supply for Norway, a country where the female labor force participation is high and the ability to adjust labor supply may be hampered by labor regulations. Thus we should expect that the importance of labor supply as insurance should be even higher in a country such as the US.

The outline of the paper is as follows. The following section presents the institutional setting and the data, Section 3 contains the estimation of income variance and correlation. Section 4 offers an empirical test of the importance of spousal labor supply for insurance, and Section 5 concludes.

3.2 Institutional setting and data

3.2.1 Institutional setting

In this section we will provide an overview of institutional details of relevance for our study, which will contribute to a better understanding of how the results for Norway may compare to other countries. More specifically we will look closer at the generosity of unemployment insurance and measures of labor market flexibility.

Unemployment insurance. Even if shocks to employment are not the focus of this paper, unemployment constitutes an important part of the income risk that the individual faces. If the state-provided unemployment insurance is a feasible alternative to household income, the importance of all insurance channels, including spousal labor supply, decreases.

Norway is among the OECD countries with the most generous welfare system and participation in welfare programs is compulsory for all residents. The most important services for adults include unemployment insurance (UI), sick money and disability pensions. When it comes to UI, there is a minimum income requirement in order to be eligible. However, this level is low by Norwegian standards and in practice all full-time employees will meet this requirement. For 2007, the amount was 100,000 Norske kroner (NOK), or around 16,000 US dollar. Workers who become unemployed are entitled to around 62 percent of their earnings in the calendar year before job loss up to a ceiling.⁶ The ceiling is always six times "grunnbeløpet" (the amount used as a basis to calculate social insurance payments).⁷ Among the individuals

⁶As pointed out by Browning and Crossley (2001), a ceiling on the insurable income of an individual implies that high-income individuals will experience a larger shock to income in case of unemployment than low-income individuals as their UI replacement rate is effectively lower.

⁷"Grunnbeløpet" changes every year to account for changes in inflation.

in our sample in year 2010, around two thirds of the individuals earn more than the ceiling. The individual can receive UI for a maximum of 2 years.⁸ When the UI expires the individual is entitled to means-tested social assistance to cover basic needs, without maximum duration.⁹

To provide a picture of the generosity of the Norwegian benefits in comparison to other countries we use calculations of benefit generosity made by the OECD.¹⁰ Their measure of gross replacement rates compares unemployment benefits received when not working to wages earned when employed and is provided for the years 2001 to 2011.¹¹ According to this measure, Norway had the highest benefit ratio of the 29 countries included in 2001 at 56 percent, followed by Denmark at 54 percent. Between 2001 and 2011, the ratio decreased and the average ratio for Norway over the whole period is 47, which is the second highest average after Denmark's 50 percent. These numbers can be compared to 11 percent for the UK and 13 percent for the US. The lowest period average is that of the Czech Republic at 6 percent.

OECD also provides a similar measure¹² that is calculated for uneven years between 1975 and 2005, but may be less comparable across countries. This measure indicates that the average Norwegian replacement rate was relatively low between 1961 and 1975 (5 percent), compared to most other countries for which there is data.¹³ However, it increased drastically between 1975 and 1977 from 8 to 21 percent. In 1981 Norway placed itself among the OECD countries with a relatively generous insurance. This means that the importance of individual and family insurance may have decreased more over time for a Norwegian than for individuals in other countries, as for example Denmark.

Labor market flexibility. The degree of labor market flexibility may be important for the impact of income shocks. A less rigid labor market in terms of employment protection legislation or a loser legislation when it comes to temporary work, may in itself cause greater insecurity regarding future income for those who work. On the other hand, it may make it easier to find a new job if exposed to a negative employment shock, as well as to facilitate for the partner to find a job in case of a negative shock to the partner's income.

In order to see how Norway compares to other countries on these factors, we use data and studies from the OECD. OECD has a much cited measure of the strictness of the employment protection legislation (EPL) of countries. The measure is a summary index taking into account

⁸Unemployed workers above the age of 64 can receive the payments until they retire at 67.

⁹The worker could also receive sick money or disability pensions, given that a medical doctor certifies that he or she cannot work, or is permanently disabled. The maximum duration of sick money is one year and is paid at a rate of 100 percent up to the same ceiling as for UI. The replacement rate of the disability insurance is around 67 percent up the same ceiling as for UI.

¹⁰See Directorate for Employment, Labour and Social Affairs. Benefits and Wages: Statistics.

¹¹More specifically, the benefits includes unemployment insurance and unemployment assistance benefits and the individual is the unit of analysis. The measure represents the average of the gross unemployment benefit replacement rates for two earnings levels (average earnings and two thirds of average earnings, for three different durations of an unemployment spell, and for three family and income situations (single, married with dependent spouse, and married with spouse in work). For more details, see [Martin \(1996\)](#).

¹²It sometimes includes also social assistance.

¹³This can be compared to for example Denmark (27), Belgium (40) and the UK (25) during the same period.

procedures and costs involved in dismissing workers. For the measure of protection of regular workers against individual and collective dismissals in 2013, Norway is at the OECD average of 2.9 out of 5. New Zealand, the US, Canada and the UK occupy the four lowest places in the ranking, while France, Netherlands, Belgium and Germany are at the top.¹⁴

When it comes to the use of permanent contracts, the share of dependent workers on permanent contracts rather than on temporary in Norway is on average 92.5 between 1996 and 2012. The OECD average during the same time period is 90.6 percent and for the UK 95.1.¹⁵ In regards to the regulation surrounding temporary contracts, Norway ranks the 4th highest of the OECD countries in terms of strictness of the regulation, while UK, US and Canada hold the three bottom positions.

The extent to which it is possible to work part time is another factor likely to contribute to the flexibility of changing work hours. According to the OECD Full-time/Part-time Employment Database, the share of part-time of total employment in Norway is quite high compared to other OECD countries.¹⁶ In 1983 it was 29.6 percent, compared to 24.8 for Sweden, and 21.2 for the Netherlands. UK had 19.0 and the US 18.4. Italy had the lowest share in this year at 4.6. The share in part-time in Norway has not followed the increasing trend seen in most other OECD countries and in 2010 it was 26.7, which is still among the highest. The only countries with higher values are Australia (29.8), Netherlands (35.2) and Mexico (27.1).¹⁷

To summarize, Norway seems to be a country with fairly rigid labor markets and generous unemployment insurance as compared to many other countries.

3.2.2 Data description

The data that we use is administrative data from the Norwegian tax registers between the years 1985 and 2010.¹⁸ The dataset covers every individual in Norway and allows us to track the income of the individuals for every year since 1985.¹⁹ Moreover, from 1993 we are able to merge this information with the financial wealth of the households through a unique personal identifier available in all registers in Norway. A couple (or a household in this context) is identified as two individuals who are married, or as two individuals who live together with common children. We can observe the latter since 1991. Unfortunately it is not possible to identify unmarried but cohabiting couples without children.

¹⁴OECD Employment Outlook (2013).

¹⁵Source OECD Labor Force Statistics. The period is from 1996 because before that data for Norway was missing. For the US, there is a lot of years missing in general.

¹⁶Note that the definitions of part-time varies a lot among countries. This is not of importance here however, as we want to provide a view of the individuals' possibility of changing their work hours within the national context.

¹⁷Even though women are contributing to most of the part-time work, also the share of males working part-time in Norway has been relatively high throughout the period, as compared to other OECD countries.

¹⁸For more information on the Norwegian administrative data in general, see [Røed and Raaum \(2003\)](#) and for more information on the wealth data in particular, see [Fagereng et al. \(2013\)](#).

¹⁹Income information is available from an earlier point in time, but financial information is only available from 1993. Why we chose 1985 will become clear with the presentation of the estimation approach.

In order to estimate the variance and the correlation of job related income risk in a household we use the labor income of each individual. Labor income includes wage income and work-related transfers, such as unemployment and sickness benefits, as well as maternity leave payments. The disposable income of the individuals, i.e. the income net of taxes, is calculated for each household using the relevant tax rates for each year. In our analysis of precautionary wealth holdings the theoretically correct measure is correlation and variance of wage shocks rather than of income. Unfortunately the dataset does not contain information on labor supply for all years such that we can calculate the wages. However, even if the labor supply reacts to shocks, it may not be to the extent that the ordering of households in the income correlation and wage correlation distribution changes. In [Fagereng et al. \(2014\)](#) we show that for the part of the dataset for which we have information on contractual hours there are some differences in the estimated wage and income correlations, but they are not very big. If anything, the main difference seems to be at younger ages.

For the main analysis we are interested in the relation between the variance and correlation of income risk and precautionary wealth holdings of the household (see Section 4). For the main analysis we use the financial wealth of the household as our measure of precautionary wealth holdings.²⁰ The household's financial wealth is defined as the sum of the financial assets of the individuals in the household, where financial assets consist of direct stock holdings, stock holdings through mutual funds, bank deposits and bond holdings. Some households have savings in pension plans, but as these plans are only payable at the age of retirement, the major part of the households in our sample will not be able to draw on these assets in times of lower income (see sample restrictions below).

One can argue that financial wealth is the most relevant wealth for the current analysis. As it is more liquid than for example housing, the individual is more likely to draw on the financial assets in times of lower income shocks than to sell the house. [Chetty and Szeidl \(2007\)](#), for example, argue that real estate will rarely be liquidated during unemployment spells because of high transaction costs. [Basten et al. \(2012\)](#) further argue that this is even more likely to be true in Norway due to special transaction taxes.

The dataset further covers a rich set of characteristics for each individual such as age, education, household size, country of origin, county, and industry of the individual. We observe these variables from 1985, except for household size and industry which we observe from 1993 onwards. The industry classification that we use throughout is the 2-digit NACE code (revision 2) and for education we will divide the individuals into fairly disaggregated categories. We have the following education groups: less than secondary education; secondary education; some high school, high school degree; university lower/vocational degree or college education; university; and research. The income and asset data is deflated using "grunobeløp i folketrygden", which is a measure accounting for the inflation used to calculate for example

²⁰In the context of precautionary savings, as pointed out by [Carroll and Samwick \(1997\)](#) it may be preferable to use the stock of wealth rather than savings. The response to income uncertainty should generally be to hold more wealth, not necessarily to depress consumption forever. In the case of the buffer stock model, the household will not save more once the optimal stock of wealth is obtained. However, households with higher income uncertainty should hold a higher stock of wealth.

social benefits.

Our initial sample consists of the population of households (as defined above) in Norway. As we have data over financial assets from 1993, we are only going to use data from that year in the analysis. However, as described below our rolling window estimation will use data from 8 years back in time for each estimation. Therefore we drop all observations before year 1985. With this restriction we have 972,465 households in our sample and 14,901,340 observations, where one observation is household h in year t . Further, we drop individuals younger than 25 and older than 60 (1,393,445 observations) and we remove observations for which information is missing on county, origin, or education (198,566 observations). As the focus of the paper is on the correlation of spousal income shocks, we restrict the sample to households where both individuals have positive labor income (less 1,709,392 observations). Note that labor income also includes unemployment insurance, maternity leave benefits, etc. We further require each household to have at least 15 years of positive income observations, which need not be consecutive (less 3,334,097 observations).²¹ The couples are allowed to break up and form new households which will be included if they conform to the other sample restrictions. The final sample consists of 405,888 households with an average number of periods per household of 21.0 years and a standard deviation of 3.6 years. The total number of observations is 8,265,854 household-years. The financial wealth as well as the income will be expressed in Norwegian kroner (NOK) throughout the document. At this time one USD equals around 6.6 NOK.

The descriptive statistics for the sample used for the variance and correlation estimations are shown in Table 3.1.²² The yearly disposable income of the females in the sample is on average lower than that of the males at 219,000 NOK compared to 351,000 NOK. The total household disposable income in the sample is on average 570,000 NOK. The average age of females is around 42.0, the average age of males is around 44.2, and the average household size is 3.8. The average number of periods (years) per households that we have for the variance and correlation estimations is 21.0 with a standard deviation of 5.4.

Table 3.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Income female	219364.8	103865.3	1.1	15540156
Income male	350660.7	205418.3	1.1	145096704
Income household	570025.5	243276.5	2.4	145209904
Age female	42.0	8.2	25	60
Age male	44.2	8.2	25	60
Household size	3.8	1.0	2	6
No of years per household	21.0	5.4	15	36

²¹Using only 10 years does not change the conclusions of the paper, but it adds more noise.

²²Note that the descriptive statistics of the sample used in the analysis of precautionary asset holdings will be presented in Section 4.

3.3 Co-movements in labor income risk

3.3.1 Estimation of income variance and correlation

In the following we will estimate the income shock correlation and variance for each household. As mentioned above, we have at least 15 non-zero observations of labor income for each individual in the household. We use the series of individual disposable incomes in a household to estimate the total variance and the correlation of household income shocks. In a first step we attempt to purge the labor income of all factors that may be predictive (to the econometrician) of the income of the individual. In order to do this we regress the natural logarithm of individual income on age and age squared, dummies for the education level, origin, county, and year, as well as the interaction of education with age and age squared and education and time.

The regression model:

$$\ln y_{h,i,t} = \beta_0 + \mathbf{X}_{h,i,t} \beta_i + \text{county}_{h,t} + \tau_t + \epsilon_{h,i,t} \quad (3.1)$$

$\mathbf{X}_{h,i,t}$ includes the observable characteristics of individual i in household h at time t , where i represents either the female or the male. τ_t is a year dummy, and $\epsilon_{h,i,t}$ is the error term. The model is estimated by OLS and from these regressions we obtain the residuals ($\hat{\epsilon}_{h,f,t}$ and $\hat{\epsilon}_{h,m,t}$).

For the estimation of the variance of total household income we use the residuals from a regression of the logarithm of total household disposable labor income (the sum of male and female disposable income) on the individual characteristics of *both* the male and the female included in the individual regressions as well as the dummies for county and time.²³

$$\ln(y_{h,f,t} + y_{h,m,t}) = \beta_0 + \mathbf{X}_{h,f,t} \beta_f + \mathbf{X}_{h,m,t} \beta_m + \text{county}_{h,t} + \tau_t + \epsilon_{h,t} \quad (3.2)$$

It is likely that the variance and correlation vary over, for example, cohort and age.²⁴ We would like to capture this in our estimates of the variance and the correlation, using the household as a basis for estimation. Therefore, rather than producing one point estimate of the variance and the correlation, we estimate the variance and the correlation using a rolling window estimation in order to obtain several estimates for each household. More specifically, for each household we estimate the variance and correlation in year, t , using the income information between $(t - 8 : t + 1)$. In order for the household to have a non-missing variance and correlation in any given year, t , the household needs a minimum of 5 years where both spouses have a positive income within the period $(t - 8 : t + 1)$. Since we observe each

²³We are not controlling for household size here as we only have data on this variable since 1993. However, we are controlling for household size in the asset regressions in the next section and below we are trying to get a notion of how labor supply may contribute to the correlation patterns.

²⁴Findings by [Blundell et al. \(2014\)](#) indicate that the variance of male income vary over age, time and education. For the co-movement in income, [Shore \(2013\)](#) shows that it tends to increase over the time in marriage. In [Fagereng et al. \(2014\)](#) we find that the correlation may vary both over cohorts, age and education.

household in the dataset for at least 15 years, one household should have at least 6 estimates for the variance and the correlation if none of the estimates are missing.²⁵

In the sample we use for the regression analysis in the next section we drop observations before 1993 as this is the year from which we have information on financial wealth of the households. With this restriction we end up with 373,209 households and 4,923,221 household-year observations. Table 3.2 displays summary statistics of the estimation results for this sample. From the bottom row we note that the average number of periods per household is around 14 years. Female income variance is higher than male income variance at 0.2 compared to 0.075. Also the standard deviation of female income variance is higher than for the male income at 0.529 compared to 0.319, although the males have a higher maximum value. The correlation is very close to zero on average with a standard deviation of 0.429.²⁶ The range of the estimated correlation is between -0.898 and 0.9. The average variance of total income, at 0.024, is lower than the average male variance which means that the variance of the male and the female possibly offsets each other to some extent together with the co-movements.

Table 3.2: Summary statistics variance and correlation of income shocks

Variable	Mean	Std. Dev.	Min.	Max.
Variance female income	0.2	0.529	0	22.263
Variance male income	0.075	0.319	0	32.55
Correlation male and female income	0.001	0.429	-0.898	0.9
Variance household income	0.024	0.07	0	6.47
No of periods per household	14.063	2.891	5	17
N	4,923,221			

3.3.2 Correlation and variance over education and industry

If assortative matching on education or industry matters for the co-movement of shocks to the spousal incomes we would expect that spouses who have the same education or who work in the same industry would on average have a higher correlation, and perhaps variance, of these shocks than spouses who do not. To study whether this is the case in our sample we compare averages of the income variance and correlation of couples who have the same education level to couples who have different education levels, as well as averages of income variance and correlation of couples who work in the same industry to couples who work in different industries. The education and industry groups are represented by the male education level and industry. As mentioned before, we only observe industry since 1993 and thus, part of our total sample is not included in the comparison of industries.

²⁵For now we do not attempt to distinguish permanent from temporary shocks to income as it requires more information. Instead we are focusing on estimating time varying measures of the variance and the correlation for each household.

²⁶The findings of Shore (2013) also indicate that the average co-movement of income shocks within a household is around 0.

We start with education. The first two columns of Table 3.3 show the mean correlation over male education groups and the two latter columns display the mean variance over the same groups. Furthermore, column 1 and 3 show averages by education level for couples who have *different* education levels and column 2 and 4 show the average estimates for the households where the spouses have the *same* education level. Note that subscript h denotes household h , and subscript m/f refers to the male/female member of the household.

Studying the correlation for households over male education levels we see that the average correlation is higher for couples with the same education than for couples with different education and this difference is significant at the 0.1 percent level.²⁷ Furthermore, the correlation displays a u-shape over the education levels; it is highest for households where the male has a low and a high level of education and lowest when the male has a high school degree. If we compare couples with a different education level (column 1) to couples with the same education level (column 2) we notice that the average correlation is higher for couples with the same education level in all cases except for high school. However, in the case of male high-school we cannot reject the hypothesis that the average correlation is the same for couples with same and different degrees. All other differences are significant at the 0.1 percent level, except for the couples with less than secondary education where the difference is not significant.

Regarding the total income variance of the household, it more or less follows the u-shaped pattern of the correlation. We may also note that the average variance for couples with same education is slightly lower than the average variance for couples with a different degree, although we cannot reject the hypothesis that they are the same. Moreover, the total variance is higher in the cases where the couple has the same education for all male education levels apart from some high school, high school and university/vocational degree. These differences are all significant. However, we cannot reject the hypothesis that the average variance is the same for the case when male has a research degree. This indicates that even if the couples with the same education tend to have a higher correlation, the average variance may be lower because of offsetting variance of the individual labor incomes.

In the next step we will do the same type of analysis over industries, which we expect to be a stronger determinant of the couple's correlation and variance of income than the education.

Table 3.4 displays the averages over industry groups. Column 1 and 2 display the correlation and column 3 and 4 show the variance. In column 1 and 3 we find averages by industries for couples who work in different industries and in column 2 and 4 we find the average estimates for couples who work in the same industry. When studying the table it is important to keep in mind that the variance displayed is not the variance of male income for each industry, but for the total household income, and thus, the variance estimate also depends on the industry of the female. Nonetheless, from column 1 we can see that in case the male works in some of the industries considered risky, such as agriculture and real estate activities, the total income variance is relatively high. If the male instead works in industries associated to the public

²⁷All the test results reported in this section are not displayed in the paper, but can be obtained by the authors upon request.

Table 3.3: Averages of variance and correlation of income shocks over male education levels

	$Mean(corr(\hat{\epsilon}_{f,t}, \hat{\epsilon}_{m,t}))$		$Mean(var(\hat{\epsilon}_{h,t}))$	
	$educ_f \neq educ_m$	$educ_f = educ_m$	$educ_f \neq educ_m$	$educ_f = educ_m$
< Secondary	0.0303	0.0470	0.0412	0.0704
Secondary	-0.0134	0.0008	0.0248	0.0276
Some High school	-0.0044	0.0166	0.0241	0.0220
High school	-0.0052	-0.0060	0.0217	0.0209
Uni lower/vocational degree	-0.0039	0.0011	0.0239	0.0223
University	0.0101	0.0739	0.0247	0.0357
Research	0.0535	0.1180	0.0294	0.0289
Total	-0.0032	0.0073	0.0236	0.0235

Note: Column (1) and (3) refer to households which have different education level, whereas column (2) and (4) refers to households with the same education level.

sector, such as public administration and defense, as well as education, the total variance tends to be lower.²⁸

Comparing the average variance of couples who work in different industries to couples who work in the same industry (column 3 and 4 Table 3.4) we note from the last row of the table that, on average, the couples working in the same industry have a slightly higher total variance and the difference is significant at the 5 percent level. Furthermore, for 12 out of the 18 industries for which a comparison is possible, couples who work in the same industry have a higher variance on average, and the difference is significant at least at the 5 percent level. The exception is electricity and gas and transportation and storage in which cases we cannot reject that the average variance is the same between the groups. In the cases where the couples working in the same industry have a lower variance (mining and quarrying, information and communication, public administration and defense, education and human health and social work), all differences are significant at the 0.1 percent level. It is interesting to note that half of these are industries associated to the public sector where we would expect a low variance.

When it comes to the correlation of couples working in the same industry, we see from column 2 that the highest correlation can be found in accommodation and food service activities (0.07), followed by agriculture, forestry and fishing (0.06). The lowest correlation for couples working in the same industry can be found in mining and quarrying (-0.04) and in electricity and gas (-0.02). Comparing column 1 to column 2 we see that, as expected, the average income correlation of couples working in the same industry is higher than the average income correlation of couples working in different industries for all industry groups. All differences are significant at the 0.1 percent level. The only industry where a comparison is not possible is for 'water, sewerage and waste management' where we, due to few observations, did not obtain an estimate for couples working in the same industry.

²⁸Although not shown for this exact sample, we know from [Fagereng et al. \(2014\)](#) that the probability of the female working in the same industry, conditional on the male working there tend to be quite high for these industries. Therefore, the averages of total income displayed in the table can be expected to be low due to low variances in individual incomes.

Table 3.4: Averages of variance and correlation of income shocks over male industry

	$Mean(corr(\hat{\epsilon}_{ft}, \hat{\epsilon}_{mt}))$		$Mean(var(\hat{\epsilon}_{ht}))$	
	$ind_f \neq ind_m$	$ind_f = ind_m$	$ind_f \neq ind_m$	$ind_f = ind_m$
Agriculture, forestry and fishing	0.0323	0.0599	0.0390	0.0433
Mining and quarrying	-0.0447	-0.0414	0.0201	0.0200
Manufacturing	-0.0192	-0.0044	0.0195	0.0201
Electricity and gas	-0.0289	-0.0211	0.0128	0.0136
Water supply, sewerage and waste management	-0.0069	-	0.0197	-
Construction	-0.0069	0.0020	0.0240	0.0250
Wholesale and retail trade	-0.0174	0.0059	0.0228	0.0253
Transportation and storage	-0.0124	-0.0062	0.0243	0.0250
Accommodation and food service activities	0.0119	0.0744	0.0347	0.0453
Information and communication	-0.0169	-0.0134	0.0173	0.0169
Financial and insurance activities	-0.0189	-0.0141	0.0160	0.0160
Real estate activities	-0.0076	0.0027	0.0330	0.0355
Professional, scientific and technical activities	-0.0050	0.0032	0.0237	0.0239
Administrative and support service activities	-0.0150	0.0007	0.0309	0.0333
Public administration and defense	0.0062	0.0229	0.0186	0.0182
Education	0.0088	0.0375	0.0223	0.0199
Human health and social work	0.0067	0.0350	0.0293	0.0286
Arts, entertainment and recreation	-0.0040	0.0121	0.0265	0.0275
Other service activities	-0.0147	0.0127	0.0261	0.0298
Total	-0.0109	0.0073	0.0227	0.0235

Note: Column (1) and (3) refer to households which have different industry classifications, whereas column (2) and (4) refers to households with the same industry classification.

From this descriptive analysis we conclude that working in the same industry and, to some extent, having the same education are important for the income risk that a household faces and could be determinants of the household's ability to use spousal labor supply as an insurance against income shocks.

In the next section we will use our measure of the household's ability to use labor supply to insure income to test whether households consider this insurance mechanism important.

3.4 Income risk and the added worker effect

3.4.1 Prediction

In the following section we provide intuition for how the ability of an individual to insure the income of her or his spouse depends on the correlation of shocks to the individuals' incomes. Based on this reasoning we will have a prediction that we will test empirically in the following subsection.

We focus on insurance through spousal labor supply adjustments, which we refer to as the *added worker effect*. To illustrate how co-movements of spousal income risk matters for this type of insurance, imagine a household with a male and a female who both work, act as a

unit and pool income within the household.²⁹ They both earn an hourly wage in the labor market and the wages of both individuals are subject to shocks. The shocks may be more or less correlated among the individuals depending on, for example, whether they work in the same industry or not.

In order to study the importance of co-movements of wage shocks for the added-worker-effect we will look closer at two cases: **a)** The labor supply is inelastic, i.e. the spouses cannot use spousal labor supply as insurance; **b)** Labor supply is elastic and the household can insure income through labor supply.

a. Inelastic labor supply. In this case changes in the co-movement of shocks simply affect the variability of household income. If, at the extreme, the spouses have identical income processes and a correlation of income shocks of -1, income pooling will eliminate all income risk. However, if the correlation is 1, there is no insurance through income pooling. Thus we expect that with inelastic labor supply, the co-movement of shocks to income only affects spousal insurance through the effect on total income variability.

b. Elastic labor supply. In this case the co-movement of wage shocks does not only affect total income variability, but also the effectiveness of the insurance through spousal labor supply. To see this, imagine that the wage of the husband has been hit by a negative shock. If the labor market situation of the wife is also negatively affected it is likely to be more difficult for her to cover part of the income loss using her labor supply, than if she was not affected by the shock. Thus, we expect that with elastic labor supply, the co-movement of shocks to spousal wages does not only affect the spousal insurance through the effect on total income variability, but also the ability to insure income through spousal labor supply.

As such, given all other insurance channels, case **a** and case **b** have different implications for the precautionary savings of a household. More specifically, in case **a**, we would expect a household with a higher correlation to save more than a household with a low correlation of shocks, all else equal. However, given the variance of total income, the correlation of wage shocks should not matter for precautionary savings.

The situation is different when labor supply is elastic, as in case **b**. First of all, we would expect precautionary savings to be lower in this case than in case **a**, but most importantly, we would expect savings to vary with the correlation of wage shocks when we control for the variance of the wage shocks. Households with a higher correlation of shocks have a lower ability to insure income through labor supply and are expected to save more than households with a low correlation of shocks, all else equal.

Therefore, with appropriate data we are able to test whether spousal labor supply is an important insurance mechanism for the household.³⁰

²⁹If the individuals in the household act as two separate units with no income pooling, the correlation of labor income shocks is irrelevant for savings. Note that the analysis only hinges on the spouses sharing a strictly positive fraction of their income.

³⁰However, if the correlation is found not to have any effect independent of the total variance, we do not

3.4.2 Empirical analysis

In this subsection we test the prediction stated above: If households use spousal labor supply to insure labor income, the correlation of income risk should affect precautionary savings independently of the variance in income shocks.

In order to test the prediction, we estimate regression models with accumulated financial wealth as the dependent variable and with variance and correlation of income shocks as independent variables, controlling for other household characteristics that are likely to be important for the asset holdings. If the coefficient on income correlation is positive and significantly different from zero it is evidence in favor of spousal labor supply being used to insure income.

In our analysis we use four different measures of financial wealth: the logarithm of total financial assets; total financial assets normalized by income; the logarithm of safe financial assets; and safe financial assets normalized by income. The safe asset category excludes direct and indirect stock holdings and thus it consists of bank deposits and bond holdings. To the extent that safe assets are more liquid than risky assets we may see a difference in the effect of income risk only including these assets.

As mentioned before, we observe financial assets of households from 1993. Given the procedure to estimate the variance and the correlation of income risk of the households using a 10 period rolling window from $t - 8$ to $t + 1$, we will with our sample from 1985 have the first variance and correlation estimates for year 1993. Since we will not use observations before 1993 in the regressions we drop these observations and are left with 373,209 households and 4,923,221 observations in total.

The descriptive statistics of the sample we use for the regressions are presented in Table 3.5. The average (disposable) household income in the sample is around 600,000 NOK. The average financial wealth per household in the sample is around 456,000 NOK. The ratio of financial wealth to disposable income is on average 0.75, but we see that maximum value is 35, indicating that most individuals in the sample has a low financial wealth to income, but that there are exceptions. The average of safe assets is around 214,000 NOK. As the minimum value of this variable is 0 we can conclude that the entire financial wealth of at least one of the households consists of stocks. The average household observation has a higher yearly income than safe asset holdings as the average is around 0.51. The average age of males is around 46 years old and of females around 44. The average household size in our sample is 3.7 individuals. We also see from the table that in 36 percent of the households the individuals have the same education category and in 18 percent of the households the individuals have the same industry classification (2-digit NACE, rev. 2).

We estimate the following regression model:

$$\ln W_{h,t} = \alpha_0 + \alpha_1 \ln Var_{h,t} + \alpha_2 Corr_{h,t} + \alpha_3 \mathbf{X}_{h,t} + \theta_t + \eta_h + \nu_{h,t} \quad (3.3)$$

where $W_{h,t}$ is one of the four measures of financial wealth, $\ln Var_{h,t}$ is the logarithm of our measure of the variance of income shocks and $Corr_{h,t}$ is the measure of the correlation of

know whether this is because labor supply is inelastic or because spouses are not pooling their income.

Table 3.5: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Household income	600265.0	162468.4	224003.1	1330590
Financial wealth	456416.5	848761.1	236.8	8339515
Ratio of financial wealth to disp. income	0.754	1.421	0.001	35.23
Safe assets	214243.7	395410.3	0	8010357
Ratio safe assets to disp. income	0.506	0.901	0	30.024
Age, male	46.4	7.4	28	60
Age, female	44.3	7.5	28	60
Household size	3.7	1.1	2	6
Share in same education	0.357	0.479	0	1
Share in same industry	0.184	0.387	0	1
Variance income	0.024	0.07	0	6.47
Variance female income	0.2	0.529	0	22.263
Variance male income	0.075	0.319	0	32.55
Correlation income	0.001	0.429	-0.898	0.9
N	4923221			

income shocks. \mathbf{X}_h is a vector of household characteristics including the logarithm of the total household disposable income, male age and age squared, dummies for household size, and for the industry and education of both spouses, as well as year dummies. Moreover, households may differ in some unobserved variable, which might also be correlated with the outcome variable. This variable is denoted by η_h and we assume that η_h is time invariant.

In a first step we estimate this model using the ordinary least squares (OLS) estimator. However, the OLS estimator is likely to be problematic for this analysis for at least two reasons. First of all, as we are using at most 10 observations for each estimate of a household's variance and correlation of income, the household variance and correlation are likely not to be precisely estimated. Thus, most probably we have a problem of measurement error in the variables of interest. Assuming that the measurement error is classical, the estimated coefficients are downward biased. In an attempt to correct for this we follow the approach in, for example, [Carroll and Samwick \(1997\)](#) and use the instrumental variables (IV) estimator.³¹ As instruments we will use the variation in couple combinations of industry over time. For example, all males that work in education with a spouse working in construction, according to the 2-digit NACE classification will be one combination, etc. More specifically, the instruments are the average income shock correlation and variance for each such industry combination at each point in time. We consider this to be an appropriate instrument as the industry combination of a couple is likely to be an important determinant of the income risk and, in

³¹However, we go about it slightly different with respect to their study. In their analysis, [Carroll and Samwick \(1997\)](#) use industry, education, and occupation for the male as well as age interactions of these variables as instruments.

addition, the influence of such a combination may change over time. The exclusion restriction is that the industry variances and correlations estimated for each spousal industry combination do not influence the financial wealth of the household other than through the household income variance and correlation. We consider this to be a plausible assumption as it is difficult to imagine how the couple combination of industry would influence the financial wealth beyond the effect on income variance and correlation once we control for the industries of the individuals.

Another potential problem with the OLS estimator is that households with a high income shock correlation or variance could be systematically different from households that have a low income correlation or variance in ways that we are not able to control for and that may be relevant for precautionary savings. That is, we have an omitted variables problem. As mentioned above, one example would be risk aversion. Households with a lower risk aversion may choose to work in more risky industries (as well as the same industry), and they may save less.³² In order to deal with the problem of unobserved heterogeneity we assume that this unobserved household-specific factor is fixed over time and we account for it using the fixed effects (FE) estimator.

Finally, in order to try to correct both endogeneity problems at the same time, we use a fourth estimator, the IV-FE estimator, which is our preferred estimator.

First stage. Before we go to the main results we show the results from the first stages. Due to the measurement error problem in our variables of interest we have two endogenous regressors in the asset regressions. In the first stages of the IV and the IV-FE estimations we predict each of these regressors using both our instruments. As stated above, the instruments we use are the average variance and correlation of income shocks over male and female industry combinations and year, denoted by $VarInd_{ct}$ and $CorrInd_{ct}$, where c denotes industry combinations (i.e. male works in education and the female in construction, etc.). Thus, the first stage equations are:

$$\ln Var_{h,t} = \gamma_0 + \gamma_1 \ln VarInd_{c,t} + \gamma_2 CorrInd_{c,t} + \gamma_3 \mathbf{X}_{h,t} + \lambda_h + \omega_{h,t} \quad (3.4)$$

$$Corr_{h,t} = \delta_0 + \delta_1 \ln VarInd_{c,t} + \delta_2 CorrInd_{c,t} + \delta_3 \mathbf{X}_{h,t} + \kappa_h + \varpi_{h,t} \quad (3.5)$$

The results from the first stages are displayed in Table 3.6. In column 1 and 2 we show the results from the first stage of the IV. We can see that our instrument for correlation is a strong predictor of the couple correlation and, similarly, from column 2 we note that the instrument for variance is a strong predictor for the variance in income shocks of the couples. Even though our instrument for variance seems to be a weak predictor of the household correlation and vice versa, we may note from the table that the F-values are very large, indicating that the instruments are strong. In column 3 and 4 we show the results from the first stage within

³²Shore (2013) finds that couples seem to display positive assortative matching on income risk, in the sense that a husband with a higher income volatility is more likely to have a wife with higher income volatility. It is not too farfetched to believe that this could be matching on risk aversion.

regression.³³ We can see that the results are similar to those in column 1 and 2, although the effect of the instruments is somewhat lower. The F-values of the instruments are still very high. Thus, these first stage results seem to indicate that our instruments are strong and we

Table 3.6: First Stage IV and IV-FE

	First stage IV		First stage IV-FE	
	(1)	(2)	(3)	(4)
	$Corr_{h,t}$	$\ln Var_{h,t}$	$Corr_{h,t}$	$\ln Var_{h,t}$
$VarInd_{c,t}$	0.001 (0.00167)	0.693*** (0.00518)	-0.002 (0.00168)	0.380*** (0.00430)
$CorrInd_{c,t}$	0.999*** (0.00830)	0.075** (0.02579)	0.613*** (0.00914)	-0.015 (0.02322)
Log disposable income	yes	yes	yes	yes
Age polynomial	yes	yes	yes	yes
Education dummies	yes	yes	no	no
Industry dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Household size	yes	yes	yes	yes
F-value (instruments)	9374	11704	2598	4578
N	4923221	4923221	4923221	4923221

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

will proceed to the main analysis of the paper

The effect of variance and correlation on precautionary wealth holdings. In the following we test whether spousal labor supply (or the added worker effect) is an important labor income insurance mechanism for households in Norway. As stated above, we will use four different outcome variables: log financial wealth, the ratio of financial wealth to disposable income, the log of safe financial assets, and the ratio of safe financial assets to disposable income. Before the regressions we winsorize the financial asset categories at the 99 percentile. This is also why the number of observations are differing slightly between the regressions of different asset categories.

The first table, Table 3.7, shows the results using log financial wealth of the household as the dependent variable. The first column displays the results of the OLS estimator from a regression of financial wealth on the logarithm of income variance and correlation. The coefficient on income variance is positive and significant, as we would expect from earlier studies. The correlation is also positive and significant, but it has a very small impact. In column 2 we see the results from the second stage of the IV regression. The impact of variance

³³Note that the education dummies drop out in the within estimation as education is fixed over time.

is now stronger. The coefficient on correlation is much stronger with this specification and indicates that the added worker effect is important for Norwegian households. However, we would still be worried about potential omitted variables bias. In column 3 we attempt to deal with this problem using the fixed effects estimator. We see that both the coefficient on the variance and the correlation becomes smaller with respect to both the IV and the OLS estimator, indicating that there might be an unobserved, household-specific variable that is positively correlated with income risk and precautionary savings. When we attempt to deal with both unobservable variables and measurement error using our preferred estimator, the IV-FE estimator, we see that both the variance and the correlation of couples' income shocks have an important impact on precautionary financial wealth of the household. A one percent change in the variance leads to 0.31 percent increase in financial wealth and one unit change in the correlation increases the financial wealth by about 42 percent³⁴. In regards to the correlation impact, moving from the lowest (= -0.9) to the highest correlation (= 0.9) in our sample is predicted to give a median increase in financial assets of 97,144 NOK, or equivalently 16 percent of yearly disposable income.³⁵ Increasing the total variance with one standard deviation, as reported in table 3.2, is predicted to give a median change in financial wealth of 146,491 NOK, corresponding to about 24 percent of yearly disposable income. Note however that the standard deviation of the total variance is about three times larger than the average value.

Table 3.8 shows the results using financial wealth normalized by income as dependent variable. The results show a similar pattern to that of financial wealth. The variance is positive and significant for all specifications with a stronger impact in the IV specifications. The results in column 4 indicate that a one percent increase in income variance increases the precautionary savings, measured by the ratio of financial wealth to income, by around 0.36. Regarding the correlation, it is now negative with a small effect when estimated by OLS, but as before the impact is much stronger, and positive, with the IV estimator. In the fixed effects estimation, correlation is again estimated to have a stronger negative impact relative to the OLS estimator. With our preferred estimator, however, we see that the correlation has a strong, positive impact, independent of the variance, on precautionary wealth holdings measured by the share of financial wealth to income. A unit change in the correlation results in an increase of 0.15 in the ratio of financial wealth to income.

In Table 3.9 we use the logarithm of safe financial assets as the dependent variable and from column 1 we see that the pattern is similar also for this wealth measure. We observe small effects from the OLS regression, and a more negative impact when controlling for a time invariant unobservable variable in column 3. In the IV estimation the effects are stronger and using our preferred estimator we obtain strong, positive effects for both variance and correlation, although we see that the effect is smaller than for total financial assets. A one percent increase in the variance of income shocks result in a 0.24 percent increase in safe asset

³⁴ $42 = 100 * (\exp 0.351 - 1)$

³⁵The correlation impact is found by predicting the financial wealth for all households, using the IV-FE estimates, assuming the all households have the highest and the lowest correlation. Then, we compute the median change in financial wealth between the two predicted values.

Table 3.7: Regressions with log of financial wealth as dependent variable

	(1)	(2)	(3)	(4)
	OLS	IV	FE	IV and FE
$\ln Var_{h,t}$	0.120*** (0.000534)	0.566*** (0.0101)	0.0575*** (0.000508)	0.307*** (0.0115)
$Corr_{h,t}$	0.00621*** (0.00165)	1.613*** (0.0353)	-0.0391*** (0.00127)	0.351*** (0.0396)
$\ln Income_{h,t}$	1.077*** (0.00308)	1.766*** (0.0133)	0.373*** (0.00297)	0.662*** (0.0119)
Age 2nd polynomial, male	yes	yes	yes	yes
Household size	yes	yes	yes	yes
Education dummies (f,m)	yes	yes	no	no
Industry dummies (f,m)	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	4923221	4923221	4923221	4921922

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8: Regressions with ratio of financial wealth to income as dependent variable

	(1)	(2)	(3)	(4)
	OLS	IV	FE	IV and FE
$\ln Var_{h,t}$	0.109*** (0.000386)	0.539*** (0.00809)	0.0430*** (0.000346)	0.362*** (0.00871)
$Corr_{h,t}$	-0.0227*** (0.00107)	1.381*** (0.0272)	-0.0311*** (0.000863)	0.148*** (0.0294)
$\ln Income_{h,t}$	0.0659*** (0.00248)	0.704*** (0.0106)	-0.509*** (0.00204)	-0.173*** (0.00901)
Age 2nd polynomial, male	yes	yes	yes	yes
Household size	yes	yes	yes	yes
Education dummies (f,m)	yes	yes	no	no
Industry dummies (f,m)	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	4824755	4824755	4824755	4822979

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

holdings and a unit change in the correlation results in an increase of around 21 percent in safe asset holdings.

Table 3.9: Regressions with log of safe assets as dependent variable

	(1)	(2)	(3)	(4)
	OLS	IV	FE	IV and FE
$\ln Var_{h,t}$	0.0781*** (0.000574)	0.334*** (0.00941)	0.0617*** (0.000608)	0.249*** (0.0133)
$Corr_{h,t}$	0.0325*** (0.00173)	0.928*** (0.0327)	-0.0421*** (0.00152)	0.190*** (0.0463)
$\ln Income_{h,t}$	0.772*** (0.00340)	1.166*** (0.0124)	0.326*** (0.00356)	0.538*** (0.0137)
Age 2nd polynomial, male	yes	yes	yes	yes
Household size	yes	yes	yes	yes
Education dummies (f,m)	yes	yes	no	no
Industry dummies (f,m)	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	4923221	4923221	4923221	4921922

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finally, in Table 3.10 we show the results from a regression using safe assets normalized by household disposable income. The same patterns as for the former regressions using the other outcome variables show up here, but with a lower magnitude of the coefficients. From column four we note that a one percent increase in the variance of income shocks leads to an increase of the ratio of safe assets to income of 0.15. The impact of the correlation is also much lower, but still positive and significant. A one unit increase in the correlation leads to a 0.07 increase in the same ratio.

From the analysis presented above we conclude that a higher variance in shocks to household income increases the precautionary asset holdings of a household. Importantly for our study, we find that the correlation of income shocks within the household has a positive impact on precautionary savings, controlling for the variance in income shocks. This indicates that spousal labor supply is an important labor income insurance channel of the households in Norway.

Additional checks. In order to make sure that the results are robust to slightly different specifications of the model we have made some additional estimations.

In the current regressions we have included the correlation of individual income risk. The correlation requires more information to estimate than the covariance and we might be worried that the measurement error problem is larger for the correlation. This should effectively be

Table 3.10: Regressions with ratio of safe assets to income as dependent variable

	(1)	(2)	(3)	(4)
	OLS	IV	FE	IV and FE
$\ln Var_{h,t}$	0.0496*** (0.000235)	0.186*** (0.00404)	0.0281*** (0.000238)	0.152*** (0.00549)
$Corr_{h,t}$	-0.00142* (0.000673)	0.475*** (0.0137)	-0.0206*** (0.000593)	0.0686*** (0.0186)
$\ln Income_{h,t}$	-0.110*** (0.00149)	0.0927*** (0.00525)	-0.353*** (0.00141)	-0.222*** (0.00560)
Age 2nd polynomial, male	yes	yes	yes	yes
Household size	yes	yes	yes	yes
Education dummies (f,m)	yes	yes	no	no
Industry dummies (f,m)	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
N	4824755	4824755	4824755	4823128

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

taken care of by the instruments, but in order to show that our main conclusion does not change using the covariance we display the results of the IV-FE estimator using the logarithm of total financial wealth as the outcome variable. The results are displayed in column 1 of Table 3.11 and we can see that both variance and covariance are positive and significant, confirming the main conclusion from above.

Another concern may be that the households who hold very little safe assets are different in ways that could influence the regression results. To make sure that this is not the case, we check the results of the IV-FE estimator using the logarithm of total financial wealth as the outcome variable, restricting the estimation to households with at least 3000 NOK in safe assets. The result is shown in column 2 of Table 3.11. As we can see the results are very similar to what is found above.³⁶

The conclusion from this analysis is that the correlation of income shocks within a household has an independent, positive impact on precautionary asset holdings of the household, controlling for income variance. As our theoretical prediction seems to hold in the data we further conclude that spousal labor supply is important for the income insurance of a household.

³⁶Importantly, [Hurst et al. \(2006\)](#) note that including business owners in the analysis increases the importance of the precautionary savings motive. The reason is that business owners tend to have a higher income variance and hold higher wealth. We have also run the regressions without self-employed individuals and it does not change the results.

Table 3.11: Additional checks

	(1)	(2)
	Safe assets > 3000	Covariance
$\ln Var_{h,t}$	0.322*** (0.0109)	0.295*** (0.00966)
$Corr_{h,t}$	0.339*** (0.0371)	
$Cov_{h,t}$		3.415*** (0.374)
$\ln Income_{h,t}$	0.645*** (0.0111)	0.607*** (0.0108)
Age 2nd polynomial, male	yes	yes
Household size	yes	yes
Education dummies (f,m)	no	no
Industry dummies (f,m)	yes	yes
Year dummies	yes	yes
N	4799996	4921922

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5 Conclusion

In this paper we investigate the importance of intra-household risk-sharing through labor supply, or the so called added worker effect. More specifically, we test the theoretical prediction that, in case households are using labor supply to smooth income shocks, the correlation of these shocks should have a positive and significant effect on savings, controlling for the variance of shocks to total household income.

In order to test this prediction we use administrative data from Norway. In a first step we estimate the variance and correlation of income shocks for each household. We find that the correlation of income shocks in the population is very close to zero on average, but that there is some important variation. In particular, couples who work in the same industry have a higher correlation of shocks than those who do not, which we would expect if the estimated correlation could tell us something about the common risk that these couples face.

Importantly, in the main analysis we find that the variation in correlation across households is not trivial from the perspective of income insurance. The results from our regression analysis show that the correlation has an impact on precautionary asset holdings, independent of the variance of income shocks. In the case where all households move from the lowest to the highest correlation documented in our sample, the predicted median change in asset holdings

is 97,144 NOK per, which corresponds to 16 percent of yearly disposable income. This suggests that spousal labor supply, or the added worker effect, is indeed important for income insurance and thus that the co-movement of income risk is important for the household's ability to insure income. This may have important implications for the design of tax and benefit systems, such as the unemployment insurance. Furthermore, it is important to emphasize that our findings relate to Norway, a country with a relatively rigid labor market and a generous welfare system. We therefore expect that our results provide a lower bound on the importance of insurance through spousal labor supply and we would expect the importance to be even greater in countries with more flexible labor markets and less generous welfare systems, as for example the US.

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