How Important is Precautionary Labor Supply?*

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Abstract

We quantify the importance of precautionary labor supply using data from the German Socio-Economic Panel (SOEP) for the years 2001-2012. We estimate dynamic labor supply equations augmented with measures for wage and unemployment risk. Our results show that workers choose on average about 2% of their hours of work or one week per year to shield against unpredictable wage shocks. This implies that about 20% of precautionary savings are due to precautionary labor supply. If self-employed faced the same wage risk as the median civil servant, hours of work would reduce by 2.93%.

Keywords Wage Risk · Labor Supply · Life Cycle · Dynamic Panel Data Models · Precaution

JEL Classification D91 · J22 · C23

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1 Introduction

Looking into a future full of unexpected events motivates many to save for a rainy day. Although the evidence is mixed, most studies find that income risk drives households to hold about 20-50% of wealth as a precaution (see, e.g., Carroll and Samwick 1998; Fossen and Rostam-Afschar 2013). Households can accumulate savings by consumption cuts (see, e.g., Dynan 1993; Gourinchas and Parker 2002); alternatively, this wealth may be the result of working longer hours. In this study, we quantify the importance of risks for hours of work, focusing on individual workers exposed to wage and unemployment risk.

Facing wage and unemployment risk, individuals may react to shocks in an *immediate* and in a *forward-looking* way: First, if a person is hit by unemployment, hours of work in that job will obviously fall to zero. However, if that person had also a second job, she might increase working hours in the remaining job to smooth income. Similarly, a person with only one job might react to a bad wage realization by working more in an immediate reaction to the shock. Second, individuals may take into account their expectation about future wage and unemployment shocks when deciding how much to work in a given period (Low 2005). Individuals with higher risk, e.g. self-employed, would work harder *before* shocks are realized to accumulate precautionary wealth. We quantify the empirical importance of the latter behavior and examine how many additional hours individuals work in anticipation of wage and unemployment risk.

Some theoretical studies suggest that such a precautionary behavior is important. Eaton and Rosen (1980) show that wage and unemployment risk increase labor supply if risk-aversion is sufficiently high. Flodén (2006) demonstrates that higher wage risk increases first period labor supply in a two-period model with endogenous savings. Pijoan-Mas (2006) compares precautionary savings to labor hours as smoothing mechanisms against uninsurable idiosyncratic labor market risk and shows in a calibration exercise that 15.2% of the working are due to lack of insurance in an incomplete markets economy. Note that this is not directly comparable to the concept of precautionary labor supply used in Flodén (2006), where additional hours of work are used to increase savings as an insurance device *before* the realization of wage risk. We focus on the concept of Flodén (2006), i.e. adjustments in hours worked to anticipated, but not yet realized risks.

Empirically, there is very little research devoted to this issue. As stated by Mulligan (1998, p. 1034), "there is no empirical evidence that precautionary motives for delaying leisure are important". Pistaferri (2003) finds that the effect of wage risk on labor supply is in agreement with the theory, but in practice negligible. In contrast, Parker et al. (2005) shows that self-employed respond to greater earnings risk by working longer hours. For the US, Kuhn and Lozano (2008) finds that hours of work are longer in jobs with higher wage inequality.

Our study is the first to provide comprehensive empirical evidence on the importance of precautionary labor supply using data from the German Socio-Economic Panel (SOEP). We build on insights on intertemporal labor supply choices from the seminal papers Heckman and Macurdy (1980), MaCurdy (1981), and Blundell and Walker (1986)[1] and connect to the literature on the importance of precautionary saving (e.g., Guiso et al. 1992; Dynan 1993; Carroll and Samwick 1997, 1998; Lusardi 1998; Gourinchas and Parker 2002; Fossen and Rostam-Afschar 2013).

We estimate the impact of wage risk and unemployment risk on hours of work of married men using SOEP data for the period from 2001 to 2012. Since it might be difficult to adjust hours instantaneously to their desired level, we specify dynamic labor supply regressions in order to capture partial adjustment. Our measure for idiosyncratic wage risk is based on the variability of previous wage realizations, similar to Parker et al. (2005). We model unemployment risk as in Carroll et al. (2003), as the predicted probability not to be working next period.

We find that workers choose on average about 2% of their hours of work or one week per year to shield against unpredictable wage shocks. This effect is economically important: considering a person who works 45 hours per week, precautionary labor supply amounts to about one week per year or in monetary terms about 552 Euro per year with a typical net wage rate of 12 Euro. If self-employed faced the same wage risk as the median civil servant, hours of work would reduce by 2.93%. We do not find evidence for the importance of unemployment risk.

To test whether our finding can indeed be interpreted as precautionary labor supply, we run wealth regressions and replicate results from the literature on the size of precautionary saving. If half of savings are precautionary, about 20% of precautionary savings are due to precautionary labor supply. This is in line with our estimate for the Frisch labor supply elasticity of about 0.25. Using this estimate in a simple two-period calibration exercise, we obtain that 22.48% of precautionary savings are due to precautionary labor supply, while 77.52% are due to consumption cuts.

The next section derives the empirical specification. Section 3 describes the construction of key variables, the data, and the empirical strategy. Section 4 presents estimates and implications of dynamic labor supply equations as well as a small investigation of precautionary savings, and section 5 concludes.

[1] See Card (1994) and Blundell and Macurdy (1999) for a survey.

2 Theoretical Considerations

Consider an individual i who maximizes the discounted sum of utility of all periods t of life in period t_0:

$$\max_{c_t,h_t} E_{t_0}\left[\sum_{t=t_0}^{T}\rho^{t-t_0}u(c_t,h_t)\right],$$

where c_t and h_t denote the choice of consumption and hours of work, respectively, in period t. ρ denotes a discount factor and u an instantaneous utility function.

The choices are constrained by the asset accumulation rule

$$a_{t+1}=(1+r_{t+1})(a_t+w_t^g h_t-c_t-M_t)$$

where a_t represent assets, r_t the real interest rate, n_t non-labor income, and M_t the tax liability. The gross wage w_t^g is stochastic.

Instantaneous utility takes the CRRA form

$$u_t=\frac{C_t^{1+\vartheta}}{1+\vartheta}-b_t\frac{h_t^{1+\gamma}}{1+\gamma},\vartheta<0,\gamma\geq 0,$$

with $b_t=\exp(\phi\Delta\Xi_{it}+\upsilon_{it})$. Ξ_{it} is a set of personal characteristics that modify tastes for work and υ_{it} is an idiosyncratic disturbance. Approximating the standard Euler equation and substituting in hours of work yields the labor supply equation (see MaCurdy 1983; Keane 2011):

$$\Delta\ln h_{it}=\frac{1}{\gamma}\Delta\ln w_{it}-\frac{1}{\gamma}\rho(1+r_t)-\frac{1}{\gamma}\ln b_{it}+e_{it}, \tag{1}$$

where w_{it} is the real marginal after tax wage rate of consumer i at age t. $1/\gamma$ is the Frisch labor elasticity and the approximation error e_{it} is a function of wage risk (see Jessen and Rostam-Afschar 2015; Low 2005; Domeij and Flodén 2006).[2] This yields the estimation equation

$$\Delta\ln h_{it}=\tilde{\beta}_1\Delta\ln w_{it}+\tilde{\beta}_2\Delta X_{it}+u_{it}, \tag{2}$$

where X_{it} contains Ξ_{it} as well as a constant and year dummies, which capture the second term in equation (1). In the empirical application X_{it} includes dummies for children of three age groups (younger than three, six or 18, respectively) in the household, year dummies, years of education, tenure, a dummy for East Germany, age, and age squared. u_{it} contains $(1/\gamma)\upsilon_{it}$ as well as e_{it}.

[2] For a slightly different derivation that incorporates the variance of wages in the labor supply equation see Pistaferri (2003).

Further, u_{it} contains a measure of wage risk, which we proxy with the terms $\sigma_{w,it}$ and $\Pr_{u,it}$. The former term denotes the within standard deviation of idiosyncratic log wages from previous years, the latter term is the predicted individual unemployment risk. Subsections 3.1 and 3.2 describe how we measure these variables empirically. With these terms the augmented static labor supply equation is

$$\Delta \ln h_{it} = \tilde{\beta}_1 \Delta \ln w_{it} + \tilde{\beta}_2 \Delta X_{it} + \tilde{\beta}_3 \Delta \sigma_{w,it} + \tilde{\beta}_4 \Delta \Pr_{u,it} + \xi_{it}, \tag{3}$$

where ξ_{it} is the redefined residual of the approximation.

The static labor supply equation is possibly misspecified because individuals might be unable to adjust their hours of work immediately following changes in wage, wage risk, or unemployment risk, e.g., because hours of work are negotiated centrally for many occupations in Germany. To allow for this possibility, we specify a partial adjustment model. Denote by $\ln h^*_{it}$ *desired* labor supply:

$$\ln h^*_{it} = \tilde{\beta}_1 \ln w_{it} + \tilde{\beta}_2 X_{it} + \tilde{\beta}_3 \sigma_{w,it} + \tilde{\beta}_4 \Pr_{u,it} + \tilde{\mu}_i + v_{it}, \tag{4}$$

where v_{it} is an error term. A simple partial adjustment mechanism employed by, e.g., Robins and West (1980); Euwals (2005); Baltagi et al. (2005), is given by

$$\ln h_{it} - \ln h_{it-1} = \theta(\ln h^*_{it} - \ln h_{it-1}), 0 < \theta < 1. \tag{5}$$

Replace (5) in (4) to obtain the dynamic labor supply specification as, e.g., in Baltagi et al. (2005):

$$\ln h_{it} = \alpha \ln h_{it-1} + \beta_1 \ln w_{it} + \beta_2 X_{it} + \beta_3 \sigma_{w,it} + \beta_4 \Pr_{u,it} + \mu_i + \omega_{it}. \tag{6}$$

The parameters of (4) can be recovered following the estimation of (6) with $\alpha = 1 - \theta$, $\beta_1 = \theta\tilde{\beta}_1$, $\beta_2 = \theta\tilde{\beta}_2$, $\beta_3 = \theta\tilde{\beta}_3$, $\beta_4 = \theta\tilde{\beta}_4$, $\mu_i = \theta\tilde{\mu}_i$, and $\omega_{it} = \theta v_{it}$ (Baltagi et al. 2005). The partial adjustment model nests the classic labor supply equation with $\theta = 1$ as a special case. θ may be interpreted as the speed of adjustment. This might be determined by costs to immediate adjustment of labor supply to desired hours or habit persistence (see, e.g., Brown 1952). Taking first differences of 6, we obtain our empirical labor supply equation:

$$\Delta \ln h_{it} = \alpha \Delta \ln h_{it-1} + \beta_1 \Delta \ln w_{it} + \beta_2 \Delta X_{it} + \beta_3 \Delta \sigma_{w,it} + \beta_4 \Delta \Pr_{u,it} + \varepsilon_{it}. \tag{7}$$

In specification (7), the short-run wage elasticity is given by $SR_{\eta_w} = \beta_1$, and the short-run wage risk elasticity by $SR_{\eta_{\sigma_w}} = \beta_3$. The corresponding long-run elasticities are $LR_{\eta_w} = \beta_1/(1-\alpha)$, $LR_{\eta_{\sigma_w}} = \beta_3/(1-\alpha)$.

3 Empirical Strategy

3.1 Measurement of Wage Risk

We use data from the Socio-Economic Panel (SOEP) described in Subsection 3.3 to construct measures for both gross and marginal net wage risk as follows.[3] In a first step, we detrend log gross wages with a regression on age, its square, education, and interactions of these variables, in order not to use variations due to predictable wage growth. In a second step, we obtain the sample standard deviation of the detrended log wage for each person for rolling sample windows of 5 years[4] following Parker et al. (2005). The idea behind this measure is that workers use past variation in idiosyncratic wages to form expectations about future risk. We denote this measure by $\sigma_{w,it}$. For the estimations, we standardize the risk measure by one standard deviation of the sample used in the regression to facilitate interpretation.

We divide our sample into blue collar workers, white collar workers, civil servants, and self-employed. Figure 1 shows how net wage risk on average evolves over the life cycle for each subgroup. Only age-occupation combinations with more than 15 observations are displayed, thus starting at the age of 35 for the selfemployed. As expected, hourly wages of self-employed are more volatile over the entire life cycle than those of employees. Blue collar workers and white collar workers have similar levels of wage risks. For most age groups, average net wage risk of civil servants is slightly lower than those of blue collar and white collar workers.

[3] We calculate marginal net wages for different measures of hours by scaling the forward difference:

$$w_{it} = \frac{M(y_{it} + \Delta y_{it}) - M(y_{it})}{\Delta y_{it}} \frac{y_{it}}{h_{it}},$$

i.e. we increase each person's labor income y_{it} by $\Delta y_{it} = 2000$ Euro. The tax liability M is calculated using the microsimulation model STSM. Jessen and Rostam-Afschar (2015) present a comprehensive overview of marginal tax rates for different households, for more information see Steiner et al. (2012).

[4] In case of missing observations, the remaining observed past wages are used.

Figure 1: Average Net Wage Risk over the Lifecycle

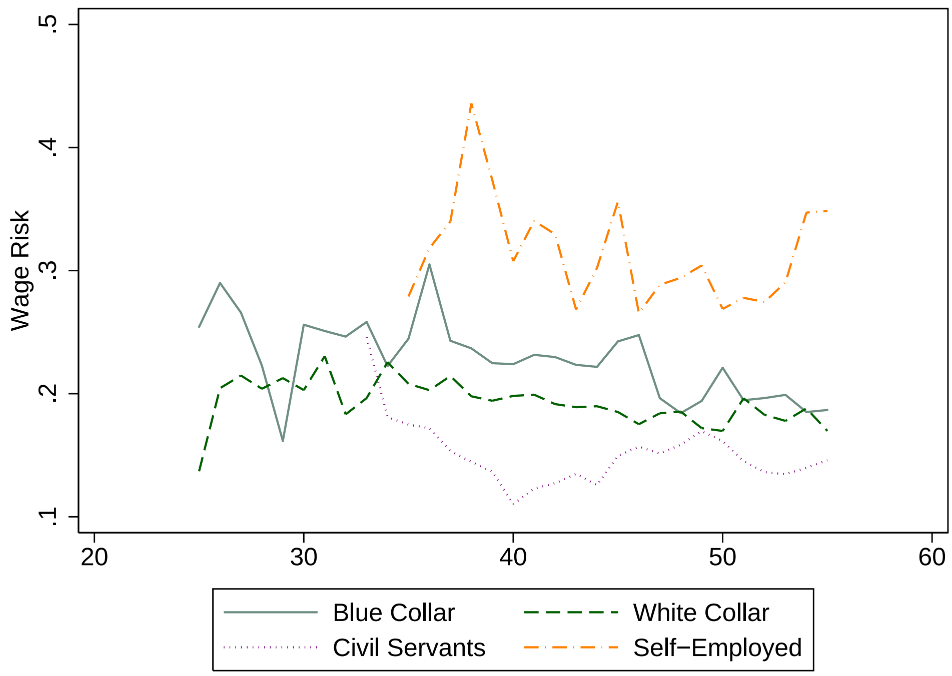
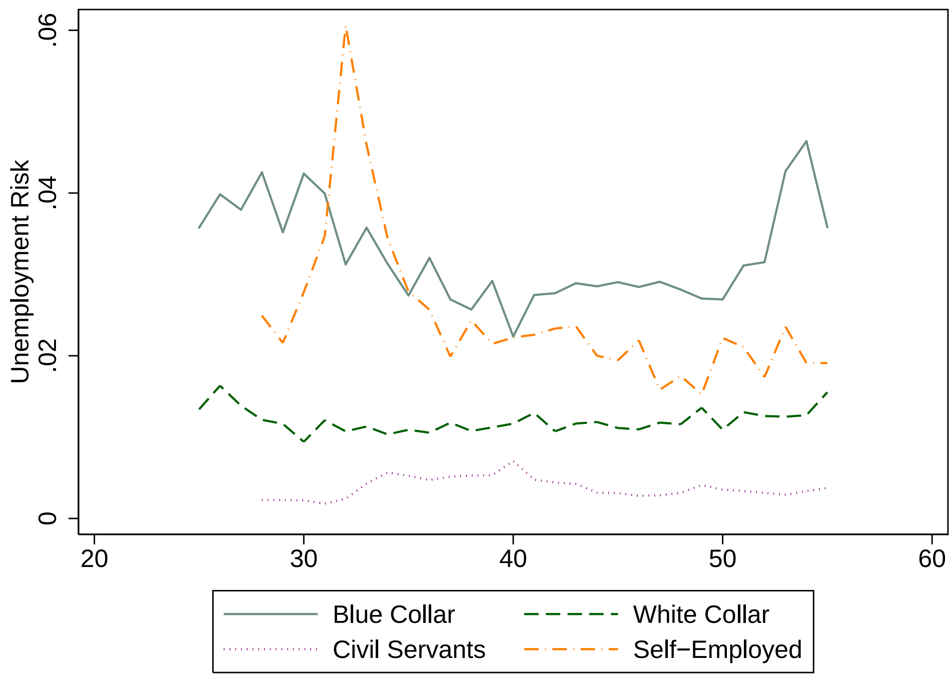


Figure 2: Average Employment Risk over the Lifecycle



3.2 Measurement of Unemployment Risk

Unemployment risk is estimated similarly to Carroll et al. (2003). For currently employed E_i individual i, we assume there exists a latent variable $U^*_{it} = Z^U_{it}\alpha_U + \zeta_{it}$ such that $U^*_{it} > 0$ if the person will be unemployed in the following year and $U^*_{it} \leq 0$ if the person will be employed. We assume ζ_{it} to be a normally distributed idiosyncratic shock that is uncorrelated with Z^U_{it}, a row vector of observable characteristics for individual i at time t. Thus $Pr(U_{it}|E_{it}, Z^U_{it}, W_{it})$ is the probability of a currently employed person to become unemployed. Following Harvey (1976), we allow the variance to vary with independent variables W_{it} such that $\sigma^2_{it} = [exp(W_{it}\gamma_U)]^2$. Therefore,

$$Pr(U_{it}|E_{it}, Z^U_{it}, W_{it}) = \Phi\left(\frac{Z^U_{it}\alpha_U}{[exp(W_{it}\gamma_U)]^2}\right),$$

where $\Phi()$ is the cumulative distribution function of a normal random variable.

We estimate this probability using data from the SOEP data. The dependent variable is an indicator that takes on a value of 1 if individual i is employed in year t and unemployed in year $t+1$, and takes on a value of 0 if individual i is employed in both periods. To proxy for the probability of an employed individual becoming unemployed, we calculate $\mathrm{Pr}_{U,it} = \Phi\left(\frac{Z^U_{it}\hat{\alpha}_U}{[exp(W_{it}\hat{\gamma}_U)]^2}\right)$, where $\hat{\alpha}_U$ and $\hat{\gamma}_U$ are the estimates of α_U and γ_U, respectively, and Z_{it} includes regressors for occupation, industry, region, education, age, age squared, age interacted with occupation and with education, marital status, unemployment experience, gender. The vector of regressors W_{it} of the heteroskedasticity function includes previous unemployment experience and years of education. This $\mathrm{Pr}_{U,it}$ is then used in our hours of work regressions as regressor. Note that we exploit the panel structure of the SOEP to estimate the conditional probability of being unemployed in the future rather than simply the unconditional probability of currently being unemployed. $\mathrm{Pr}_{U,it}$ can be thought of as a rational expectation of the odds of a currently employed individual being unemployed one year from now conditional on Z^U_{it} and is therefore an estimate of this measure of unemployment risk.[5]

Figure 2 displays how unemployment risk on average evolves over the life cycle for four occupational groups. As in Figure 1, only age-occupation combinations with more than 15 observations are displayed. Civil servants have the lowest average unemployment risk, followed by white collar workers. For most parts of the life cycle, blue collar workers face the highest average unemployment risk.

[5] We also considered an alternative measure of unemployment risk based on unemployment rates for specific cells (East or West Germany, calendar year, three education categories, five age categories). However, both measures lead to similar results.

3.3 Data

Our study is based on data from the SOEP long version 30, a representative annual panel survey in Germany. Wagner et al. (2007) provide a detailed description of the data. We use observations from the years 2001-2012. The sample is restricted to prime age (older than 25 and younger than 56) married men working at least 20 hours. We restrict the analysis to men because the extensive margin plays an important role for labor supply decisions of women complicating the analysis considerably. Further, we drop persons who indicated having received unemployment or social assistance. A summary of the number of observations lost due to each sample selection is provided in Table 8 in the Appendix. Table 1 provides weighted summary statistics of the most important variables including wage and unemployment risk measures. In total, we observe 11,061 data points, from 6,669 persons. There are slightly less observations for hours of paid overtime work than for other variables because survey participants either did not provide an answer to the question or did not have a contractual number of weekly hours of work.

In the first line we report the average hours worked per week, 45 in our sample. We restrict our sample such that the person providing fewest hours works more than typically specified in part-time contracts and we do not allow weekly hours of work to exceed 80. About 20% of the sample work paid overtime. Hourly wage is constructed by dividing gross annual labor income by hours worked in the respective year.[6] This and other monetary variables are converted to 2010 prices using the consumer price index provided by the Federal Statistical Office. Marginal net wages are the wages after taxes calculated at the margin with the microsimulation model STSM.

The last three variables in Table 1 show that our sample has 7.5% self-employed, about 28% blue collar workers, and about 51% white collar workers. Self-employed comprise free-lance professionals, and other self-employed. Blue collar workers include untrained and trained workers. White collar workers include managers, employees with simple tasks, untrained and trained employees with simple tasks, qualified and highly qualified professionals, as well as and managerial staff.

[6]Labor earnings include wages and salary from all employment including training, self-employment income, and bonuses, overtime, and profit-sharing.

Table 1: Summary Statistics

	Unit	Mean	Std. Dev.	Min	Max	N
Labor Supply						
Weekly Hours Worked	(h)	44.99	7.94	20	80	11061
Paid Overtime Work	(%)	17.34	37.86	0	100	11061
Paid Overtime Work	(h)	0.81	2.57	0	41	10971
Wages and Incomes						
Hourly Gross Wage	(Euro)	21.30	9.65	2.27	97.43	11061
Hourly Marginal Net Wage	(Euro)	12.33	5.88	1.09	57.67	11061
Monthly Gross Labor Income	(Euro)	3921.15	2064.39	319	27000	11061
Monthly Net Labor Income	(Euro)	2562.97	1254.82	150	12072	11061
Wage and Unemployment Risk						
Gross Wage Risk	(ln Euro)	0.146	0.138	0	1.698	11061
Marginal Net Wage Risk	(ln Euro)	0.201	0.156	0	1.712	11061
Unemployment Risk	(%)	1.3	2.2	0	29.9	11061
Demographics and Characteristics						
Age	(a)	44	7	25	55	11061
Years of Education	(a)	12.9	2.8	7	18	11061
Tenure	(a)	15.2	9.6	0	42.8	11061
Children younger than 3 years	(%)	8.8	28.3	0	100	11061
Children younger than 6 years	(%)	14.2	34.9	0	100	11061
Children younger than 18 years	(%)	50.8	50	0	100	11061
East Germany	(%)	13.8	34.5	0	100	11061
Type of Work						
Self-employed	(%)	7.5	26.3	0	100	11061
Blue Collar	(%)	28.3	45	0	100	11061
White Collar	(%)	50.8	50	0	100	11061
Civil Servant	(%)	13.4	34	0	100	11061
One-Digit International Standard Classification of Occupations (ISCO)						
Managers	(%)	11.5	31.9	0	100	11061
Professionals	(%)	23.2	42.2	0	100	11061
Technicians	(%)	20.8	40.6	0	100	11061
Clerks	(%)	8.0	27.1	0	100	11061
Service and Sales	(%)	4.7	21.1	0	100	11061
Craftsmen	(%)	18.7	39	0	100	11061
Operatives	(%)	9.7	29.6	0	100	11061
Unskilled	(%)	3.4	18	0	100	11061

We follow Euwals (2005) to calculate paid actual hours. To do this, we approximate
$hp_{it} = hc_{it} + I(or_{it} = A)(ht_{it} - hc_{it}) + 0.5I(or_{it} = C)(ht_{it} - hc_{it})$,
with $I(or_{it} = A)$ an indicator function for individual i at time t giving answer A (all overtime work is paid) to the question on the overtime rule. In case of answer C (some overtime work is paid), we assume that half of the overtime is paid.

3.4 Instrumentation and Estimation Methods

To estimate equation (7), we need to account for several endogeneity problems. First, the first difference of the lagged dependent variable is correlated with the error term ε_{it} which includes shocks from $t-1$. We follow Anderson and Hsiao (1981) and solve this problem by applying the method of instrumental variables where we use the level $\ln h_{it-2}$ as excluded instrument (2SLS). In an alternative specification, we exploit additional moment conditions as suggested by Douglas Holtz-Eakin (1988) and Arellano and Bond (1991) and apply the two-step difference GMM estimator (DIFF-GMM) with Windmeijer (2005) finite-sample correction. Arellano and Bover (1995) and Blundell and Bond (1998) show that the efficiency of the estimates is improved by imposing additional restrictions on the initial values of the data generating process and using lagged levels as well as lagged differences as instruments. We also present the results from this estimator known as system GMM (SYS-GMM).

Second, marginal net wage may be endogenous for two reasons. Measurement error in hours leads to downward denominator bias in the coefficient of wage as the hourly wage is calculated by dividing labor income by the dependent variable hours of work (c.f. Altonji 1986; Keane 2011). Moreover, the marginal net wage depends on the choice of hours because of the nonlinear tax and transfer system. Therefore, we instrument marginal net wages with the first lag of net labor income. This variable is predetermined at the time of current period labor supply choices and uncorrelated with the measurement error in current period hours.

4 Results

4.1 The Impact of Wage and Unemployment Risk on Weekly Hours of Work

Table 2 presents results of the augmented labor supply equation for different estimators, where the dependent variable is log hours of work.[7] Standard errors are robust. Columns 1-3 show results for the static specification, while columns 4-6 show results for the preferred dynamic specification (7).[8] The first column displays results for OLS. The coefficient of net wage is significantly negative, which is not in line with theoretical predictions and likely to be a result of the denominator bias described in Subsection 3.4. The main coefficient of interest is the one of wage risk. The

[7]Table 11 in the appendix shows results for alternative definitions of hours of work.

[8]Table 10 in the appendix shows the equivalent table using gross wages instead of marginal net wages.

coefficient of 0.014 indicates that an increase of wage risk by one standard deviation would lead to an increase of labor supply by 1.4%. The coefficient of unemployment risk indicates that an increase in unemployment risk by one standard deviation leads to a decrease in work hours by 2.5%. Both coefficients are statistically significant at the 1-% level.

Column 2 shows results for the pooled 2SLS estimator, where net wage is instrumented with lagged net labor income to overcome the denominator bias. As expected, the sign of the coefficient of net wage becomes positive, the coefficient of wage risk remains significantly positive with a point estimate of 0.024, while unemployment risk becomes insignificant. Column 3 displays results obtained with the first difference estimator with the equivalent instrument for net wages. The coefficient of wage risk remains significantly positive and all other coefficients become insignificant.

Results for the dynamic specification are displayed in columns 3-5 with the Anderson-Hsiao estimator displayed in column 3 and results for the Difference and System GMM estimators displayed in columns 4 and 5. The static specification is rejected with all three estimators with point estimates of lagged hours of work between 0.15 and 0.18. For all three dynamic estimators, the coefficient of wage risk is statistically significant. The magnitude of this effect is similar across all dynamic specifications and close to the results of the static specifications. Unemployment risk does not show significance in either of the dynamic specifications. The coefficient of marginal net wage is significant only for the system GMM estimator implying a short run elasticity of 0.21 and a long run elasticity of 0.25. For the difference and system GMM estimators, autocorrelation and Hansen tests are reported below the estimates. The Null-hypothesis of no autocorrelation of second order cannot be rejected and the Hansen overidentification test does not indicate invalidity of instruments.

Table 2: Labor Supply Regressions With Alternative Instrumentation Stategies

	OLS	2SLS	FD-IV	Anderson-Hsiao	DIFF-GMM	SYS-GMM
Lag of Actual Hours				0.189***	0.185***	0.156***
				(0.037)	(0.037)	(0.035)
Net Wage Risk	0.014***	0.024***	0.009*	0.013**	0.010**	0.018***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)
Unempl. Risk	-0.025***	-0.005	0.001	-0.002	-0.001	-0.003
	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.005)
Net Wage	-0.017*	0.234***	-0.051	-0.043	-0.041	0.210***
	(0.009)	(0.016)	(0.034)	(0.037)	(0.035)	(0.019)
Controls	✓	✓	✓	✓	✓	✓
Instruments	—	labin_{it-1}	$\Delta\text{labin}_{it-1}$	$\ln h_{it-2}$, $\Delta\text{labin}_{it-1}$	$\ln h_{it-2},\ldots,\ln h_{it-13}$, collapsed, $\Delta\text{labin}_{it-1}$	$\ln h_{it-2},\ldots,\ln h_{it-13}$, $\Delta\ln h_{it-2},\ldots,\Delta\ln h_{it-13}$, collapsed, $\Delta\text{labin}_{it-1}$
Observations	11,201	10,873	8,197	8,142	8,142	10,786
AR(1) in FD					0.000	0.000
AR(2) in FD					0.304	0.889
Hansen					0.806	0.518

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Importance of Precautionary Labor Supply

With our estimates of the wage risk semi-elasticity we can quantify the importance of precautionary labor supply in a ceteris paribus exercise. We use the estimates to simulate the distribution of hours that would realize if all individuals faced the same, small wage risk. We construct this simulated counterfactual $\hat{h}_{it}$ from a prediction of equation (7) with minimum sample wage risk $\sigma_{w,it}^{\min}$. Then we compare actual hours of work h_{it} observed in the data with their simulated counterfactuals. The difference gives us a measure of the magnitude of precautionary labor supply and, for the short run, is calculated as

$$\hat{h}_{SR,it} - h_{it} = -\beta_3(\sigma_{w,it} - \sigma_{w,it}^{\min}) \tag{8}$$

Figure 3 shows three points for each individual in the sample in 2011. The first point (p_i, h_i), denoted by a small circle, indicates the percentile ranking p_i for individual i in the actually observed distribution of hours of work (vertical axis) and h_i indicates the actual hours of work (horizontal axis) for individual i. The second point $(p_i, \hat{h}_{SR,i})$ keeps the percentile ranking p_i from the observed distribution and indicates the simulated *short-run* value of the hours of work $\hat{h}_{SR,i}$ when $\sigma_{w,it}$ is set to the value of $\sigma_{w,it}^{\min}$. The third point $(p_i, \hat{h}_{LR,i})$ shows as before p_i from the observed distribution and indicates the simulated *long-run* value of the hours of work $\ln \hat{h}_{LR,i}$ when $\sigma_{w,it}$ is set to the value of $\sigma_{w,it}^{\min}$.

$$\hat{h}_{LR,it} - h_{it} = -\frac{\beta_3}{1-\alpha}(\sigma_{w,it} - \sigma_{w,it}^{\min}) \tag{9}$$

The short-run simulated hours lie to the left of the actual hours distribution. The horizontal difference between short-run simulated points and observed points indicates by how much hours of work would reduce in the short run, if wage risk were reduced to the minimum level. The long-run simulated hours lie to the left of both the actual hours distribution and the short-run simulated points. The horizontal difference between long-run simulated points and observed points indicates by how much hours of work would be reduced in the long-run, if wage risk were reduced to the minimum level. The horizontal difference between simulated points in the long-run and short-run indicates how much of the adjustment in hours would occur after the immediate reaction to the wage risk reduction.

Table 3 reports by how much labor supply would be reduced in the short run (columns 1 and 2) and the long-run (columns 3 and 4) if wage risk were reduced to the sample minimum (columns 1 and 3) or the mean wage risk of civil servants (columns 2 and 4). Again, keep in mind that this is a

Figure 3: Reduction in Hours

Table 3: Percentage Reduction for Different Occupations

	Short-Run		Long-Run	
	Perfect Foresight	Civil Servants	Perfect Foresight	Civil Servants
All	1.81	0.68	2.14	0.80
Self-Employed	3.60	2.49	4.24	2.93
White Collar	1.70	0.56	2.00	0.66
Blue Collar	1.67	0.54	1.98	0.64
Civil Servants	1.56	0.42	1.84	0.50

ceteris-paribus exercise neglecting general equilibrium effects. In our sample hours of work would reduce by 2.14% in the long run if wage risk were reduced to the sample minimum. Defining precautionary labor supply as the difference between hours worked in the status quo and in the absence of wage risk and given the average 45 weekly hours of work in our sample, precautionary labor supply amounts on average to 0.96 hours per week. This is effect is economically important, particularly for self-employed, a group that faces average wage risks substantially above the sample mean. This group works 4.24% of hours of work because of a precautionary motive.

If instead wage risk were reduced to the average wage risk of civil servants, labor supply would decrease on average by 0.8% in the long run. For the self-employed the long-run labor supply reduction would still amount to 2.93%. If wage risk of all civil servants were reduced to its median, labor supply of civil servants would decrease by 0.5%.[9]

4.3 Results by Occupations

Table 2 above provides evidence for the significance of precautionary labor supply for all working married men. In this section, we show additional evidence for some occupational subgroups. Table 4[10] provides separate results for different occupational groups using the system GMM estimator with the same instruments as in Table 2. While the point estimate of the wage risk coefficient is positive for all four occupation groups, it is statistically significant only for white collar workers (1-% level). The point estimate is largest for self-employed (0.016) and smallest for civil servants. Given the relatively large confidence intervals, the importance of precautionary labor supply cannot be rejected for any of the groups. The wage coefficient is positive for all groups and significant

[9]This effect would equal zero if the distribution of wage risk were symmetric for civil servants.

[10]Results obtained using gross wages instead of net wages can be found in Table 9 in the appendix.

Table 4: System GMM Labor Supply Regressions for Occupational Groups

	Self-Employed	White Collar	Blue Collar	Civil Servant
Lag of Actual Hours	0.183	0.176***	0.156**	0.180**
	(0.127)	(0.045)	(0.068)	(0.079)
Net Wage Risk	0.016	0.012***	0.007	0.001
	(0.014)	(0.004)	(0.005)	(0.008)
Unempl. Risk	-0.009	-0.007	-0.005	-0.003
	(0.015)	(0.005)	(0.005)	(0.007)
Wage	0.071	0.200***	0.097**	0.273**
	(0.049)	(0.020)	(0.041)	(0.115)
Controls	✓	✓	✓	✓
Observations	950	5,886	2,430	1,520
AR(1) in FD	0.000	0.000	0.000	0.000
AR(2) in FD	0.762	0.876	0.309	0.443
Hansen	0.101	0.387	0.589	0.547

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for all but the self-employed for whom there are relatively few observations. As in the estimation using the entire sample, neither the AR(2) test nor the Hansen test are rejected.

Table 5 shows system GMM estimates of the dynamic labor supply equation for eight professions grouped according to the International Standard Classification of Occupations (ISCO 88). Each of the one-digit ISCO groups may be populated by several of the occupational classifications we used above, i.e. some managers are self-employed, some not. The Null-hypothesis that wage risk does not affect labor supply is rejected for managers, professionals, technicians, and operatives. The coefficient of net wage is significantly positive for all but the unskilled. Both the coefficients of net wage risk and of net wage are of similar magnitude as the ones obtained in the estimation using the main sample.

Table 5: System GMM Labor Supply Regressions for ISCO Groups

	Managers	Professionals	Technicians	Clerks	Service and Sales	Craftsmen	Operatives	Unskilled
Lag of Actual Hours	0.140*	0.229***	0.231***	0.148	0.137	0.0507	0.150	0.532**
	(0.083)	(0.062)	(0.069)	(0.125)	(0.231)	(0.082)	(0.112)	(0.259)
Net Wage Risk	0.027***	0.016***	0.013**	0.006	0.012	0.012	0.037**	0.011
	(0.009)	(0.006)	(0.006)	(0.005)	(0.013)	(0.009)	(0.017)	(0.012)
Unempl. Risk	0.022**	-0.001	-0.004	-0.011	-0.016	0.003	-0.010	-0.007
	(0.009)	(0.007)	(0.006)	(0.009)	(0.017)	(0.006)	(0.013)	(0.008)
Wage	0.195***	0.233***	0.149***	0.142***	-0.004	0.221***	0.178**	0.002
	(0.046)	(0.044)	(0.030)	(0.042)	(0.080)	(0.058)	(0.079)	(0.089)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,357	3,217	2,199	763	423	1,730	813	284
AR(1) in FD	0.000	0.000	0.000	0.000	0.073	0.000	0.000	0.039
AR(2) in FD	0.420	0.964	0.936	0.741	0.247	0.202	0.180	0.946
Hansen	0.756	0.106	0.545	0.401	0.0395	0.722	0.816	0.316

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Precautionary Overtime

We explore whether paid overtime work is used to adjust to wage risk. To do so, we estimate the same labor supply equation as in the previous Subsections by system GMM, but use a dichotomous dependent variable indicating whether the individual worked paid overtime hours.

Table 6 displays results for the sample of all employees as well as three occupational groups. The lagged dependent variable is significantly positive at least at the 5% level for all groups but civil servants indicating persistence of paid overtime work. The coefficient of the measure for unemployment risk is significantly positive for the sample of all employees with the point estimate implying a 5-percentage-points increase in the probability to work paid overtime if unemployment risk increases by one standard deviation. However, the wage risk coefficient is insignificant for all four groups, although the point estimates are positive for all but civil servants.

Moreover, the null-hypothesis of no second order autocorrelation is rejected for the samples of all employees and white collar workers casting doubts on the validity of the estimates. To sum up, while we do not find any evidence for the use of paid overtime work to shield against wage risk, this possibility cannot be ruled out given the positive point estimates and large confidence intervals.

Table 6: System GMM Dynamic Linear Probability Model for Paid Overtime Work

	Employees	White Collar	Blue Collar	Civil Servant
Lag of Paid Overtime Work	0.107***	0.120***	0.113**	0.0136
	(0.0305)	(0.0404)	(0.0527)	(0.107)
Net Wage Risk	0.00829	0.0109	0.0146	-0.0197
	(0.0105)	(0.0133)	(0.0369)	(0.0242)
Unempl. Risk	0.0519***	0.0298	0.0679	0.0101
	(0.0199)	(0.0218)	(0.0486)	(0.00712)
Wage	-0.0601	-0.111	-0.0676	-0.130
	(0.126)	(0.176)	(0.217)	(0.190)
Controls	✓	✓	✓	✓
Observations	7525	4603	1714	1208
AR(1) in FD	0.000	0.000	0.000	0.004
AR(2) in FD	0.00259	0.00890	0.172	0.506
Hansen	0.000243	0.000722	0.0918	0.265

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Does Precautionary Labor Supply Show Up in Savings?

In this Subsection we test whether our results for precautionary labor supply shows up in precautionary saving. If our findings can be interpreted as evidence for precautionary labor supply, the only reason to work these additional hours is to save more. Therefore, precautionary savings must be influenced by the measure of wage risk that also affected labor supply. We test this restriction by regressing log net wealth[11] on wage risk, unemployment risk, log of disposable household income and the same control variables as in Subsection 4.1.

Table 7 presents estimates obtained using the first-difference estimator (1-DIFF) and the fixed effects estimator (Fixed Effects). The coefficient of wage risk can be interpreted as the percentage change in net wealth if wage risk increases by one sample standard deviation. The point estimate suggests that this effect is about 3%. A comparison between actual net wealth and counterfactual net wealth at minimum wage risk shows that precautionary savings amount to about 7,011 Euro

[11]Net wealth is the sum of housing and other property (minus mortgage debt), financial assets, the cash surrender value of private life and pension insurance policies, tangible assets, and the net market value of commercial enterprises, minus debt from consumer credit. In what follows, we use the 5 implications provided by the SOEP according to Rubin's rule (Little and Rubin 1987; Rubin 1987).

Table 7: Precautionary Savings with Imputed Net Wealth

	1-DIFF	Fixed Effects
Wage Risk	0.029	0.025
	(0.104)	(0.105)
Unempl. Risk	0.986	0.985
	(0.439)	(0.440)
Disposable Income	0.025	0.029
	(0.344)	(0.345)
Controls	✓	✓
Observations	442	1,623

Net wealth is observed in survey years 2002, 2007, and 2012. For our sample (see Table 8) the mean over the 5 implications of the weighted mean of this variable is 239,008 2010 Euro, the median 175,844 2010 Euro, the standard deviation 297,862 2010 Euro.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and 7,729 Euro with fixed effects and first differences, respectively. This amount covers average consumption expenditures for about 2-3 month. However, the standard errors are too large to obtain statistical significance.

Even though our estimates are statistically insignificant, the confidence interval includes findings from the literature. Fuchs-Schündeln and Schündeln (2005); Bartzsch (2008); Geyer (2011) all find about 20% precautionary savings with SOEP data based on financial wealth. Guiso et al. (1992) estimate the precautionary component of net wealth at only a 2%. Lusardi (1998) uses net wealth as well and finds precautionary wealth of 1% to 3.5%. Lusardi (1997); Carroll and Samwick (1998) estimate the precautionary component of wealth for Italian and U.S. households, respectively, to be in the range of 20-50%.

In our sample, monthly savings are about 450 Euro on average. Assuming that 50% of these savings are due to the precautionary motive implies that overall precautionary savings amount to 225 Euro per month. Table 1 shows that men in our sample work on average about 45 h per week and earn an hourly marginal net wage of about 12 Euro. Then, with our result for the share of precautionary weekly hours from Table 3, 2%, precautionary savings due to precautionary labor supply are about 46 Euro per month. This means that the importance of precautionary labor supply for precautionary savings is about 20%.[12]

This result is consistent with a simple simulation exercise of a two-period version of our model in section 2.[13] We set certain wage in the first period to 12 Euro. In the second period wage realizations of 7 Euro or 17 Euro are possible with equal probability. The Frisch labor supply elasticity $1/\gamma$ is taken from the main results to be 0.25. We calibrate the coefficient of relative risk aversion ϑ and the parameter b to match the observed mean weekly hours of work. The respective values of the parameters are -1.1, and 3×10^{-9}. We restrict the discount rate ρ to one and the interest rate r to zero. Therefore, the precautionary motive is the only reason to save.

We solve algebraically for the optimal solution both under uncertainty and certainty, where the second period wage is 12 Euro. Under certainty, first period labor supply $h_1 = 44.67$ weekly hours, second period labor supply $h_2 = 44.67$ weekly hours, and savings $s = 0$ Euro. Under uncertainty, first period labor supply $h_1 = 45.71$ weekly hours, second period labor supply $h_2 = 43.61$ weekly hours, and savings $s = 55.42$ Euro. The difference in first period labor supply under uncertainty and under certainty gives precautionary labor supply per week. In this simulation, this is 1.04 weekly hours, which is in line with the results in section 4.2. With the hourly wage of 12 Euro, this implies that 22.48% of precautionary savings are due to precautionary labor supply. In this simulation 77.52% are due to consumption cuts.

5 Summary and Conclusions

We quantify the importance of wage risk and unemployment risk to explain trends in hours of work of men. We find that workers choose about 0.96 hours per week to shield against unpredictable wage shocks in German Socio-Economic Panel (SOEP) data for the period from 2001 to 2012.

Results from dynamic labor supply regressions show that workers adjust hours of work with changes in idiosyncratic wage risk, while we do not find any evidence for the importance of unemployment risk. This effect is statistically significant for white collar workers, managers, and professionals. The point estimate for self-employed is relatively large, but due to the small sample size it is not statistically significant.

This effect is economically important, particularly for self-employed, a group that faces average wage risks substantially above the sample mean. This group works 4.24% of their hours of work because of a precautionary motive.

[12] A month has 4.3 weeks on average.

[13] We assume that second period labor supply is chosen before wages realize.

Even though wage risk might be associated with labor supply, it is only possible to interpret this as evidence for *precautionary* labor supply, if savings react to wage risk as well. Therefore, we run wealth regressions and replicate results from the literature on the size of precautionary saving. While the resulting coefficients are not statistically different from zero, the confidence intervals include results from the literature. Assuming that about 50% of savings are motivated by precautionary reasons, we show that about 20% of precautionary savings are due to precautionary labor supply.

Our estimates of the dynamic labor supply regressions imply that the Frisch labor supply elasticity is about 0.25. We use this value in a simple calibration exercise using a two period model. We find that 22.48% of precautionary savings are due to precautionary labor supply, while 77.52% are due to consumption cuts in our simulation.

We conclude that precautionary savings is relevant for the political debate on social security provisions. If self-employed faced the same wage risk as civil servants, hours of work would reduce by 2.93%. For all workers excluding civil servants, labor supply would decrease on average by 0.8% in the long run. While this could theoretically be put into practice by adopting the remuneration schemes of civil servants in other occupations, this might have undesirable effects economic growth.

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6 Appendix

A Sample Restrictions

We restrict the sample drawn from the SOEP to ensure that observed fluctuations in hours and wages over the sample period of 2001-2012 are not influenced by demographic transitions. The numbers of observations eliminated with each such restriction or by missing values for key variables are given in Table 8.

Table 8: Sample Restrictions.

Full sample: 416,241 person years	*Eliminated*	*Remaining*
Incomplete interviews	276,634	139,607
Drop if female	66,588	73,019
Drop if not married	28,698	44,321
Drop if younger than 26 or older than 55 in each year	10,694	33,627
Drop if in military or agriculture	609	33,018
Drop if transfer recipients	2,700	30,318
Drop if very low hours worked	291	30,027
Drop if unrealistic hours changes	35	29,992
Drop if unrealistic wage changes	390	29,602
Drop if without net wage or risk	18,028	11,574

B Results using Gross Wages

Table 9: Occupational Groups, System GMM, Gross Wages

	Self-Employed	White Collar	Blue Collar	Civil Servant
Lag of Actual Hours	0.131*	0.207***	0.172***	0.147*
	(0.0732)	(0.0387)	(0.0419)	(0.0864)
Wage Risk	0.0149	0.0103***	0.0108***	0.00699
	(0.00977)	(0.00354)	(0.00341)	(0.00736)
Unempl. Risk	-0.0185*	0.00145	-0.000790	-0.00119
	(0.00967)	(0.00645)	(0.00311)	(0.00661)
Wage	0.0509	0.201***	0.0850**	0.245**
	(0.0365)	(0.0215)	(0.0349)	(0.113)
Controls	✓	✓	✓	✓
Observations	1454	6965	4467	1624
AR(1) in FD	0.000	0.000	0.000	0.000
AR(2) in FD	0.0428	0.504	0.831	0.482
Hansen	0.634	0.612	0.954	0.521

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Comparison of Specifications, Gross Wages

	OLS	2SLS	FD-IV	FD-IV	DIFF-GMM	SYS-GMM
Lag of Actual Hours				0.187***	0.190***	0.183***
				(0.0340)	(0.0339)	(0.0271)
Wage Risk	0.0307***	0.0376***	0.00634	0.00935	0.00707	0.0286***
	(0.00358)	(0.00438)	(0.00578)	(0.00671)	(0.00611)	(0.00357)
Unempl. Risk	-0.0153***	-0.00180			-0.00760	-0.00151
	(0.00491)	(0.00502)			(0.00627)	(0.00401)
Wage	-0.0666***	0.200***	0.0127	0.0299	0.0289	0.174***
	(0.00983)	(0.0149)	(0.0234)	(0.0260)	(0.0256)	(0.0164)
Controls	✓	✓	✓	✓	✓	✓
Instruments	—	y_{it-1}	Δy_{it-1}	$\ln h_{it-2}, \Delta y_{it-1}$	$\ln h_{it-2}, \ldots, \ln h_{it-13}$ collapsed	$\ln h_{it-2}, \ldots, \ln h_{it-13}$, $\Delta \ln h_{it-2}$ collapsed
Observations	15168	14645	11106	11018	11018	14510
AR(1) in FD					0.000	0.000
AR(2) in FD					0.0934	0.0963
Hansen					0.832	0.412

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Sensitivity of Results

Annual hours is an alternative hours worked variable from the SOEP, with slightly different imputations used. *Contracted hours* are directly aksed from the respondents. To calculate actually *paid hours*, we follow Euwals (2005): we approximate

$$hp_{it} = hc_{it} + I(or_{it} = A)(ht_{it} - hc_{it}) + 0.5I(or_{it} = C)(ht_{it} - hc_{it})$$

with $I(or_{it} = A)$ an indicator function for individual i at time t giving answer A (all overtime work is paid) to the question on the overtime rule. In case of answer C (some overtime work is paid)w, we assume that half of the overtime is paid. We also estimate a model with self-reported *desired hours* of worked. Desired hours show not be constrained by partial adjustment or state dependency, hence, es estimate this specification, using a static model.

Table 11: Alternative Hours Definitions

	Annual Hours	Paid Hours	Contracted Hours	Desired Hours
Lag of Hours	0.171***	0.225***	0.418***	
	(0.0392)	(0.0684)	(0.142)	
Wage Risk	0.0202***	0.0180***	-0.00138	0.140***
	(0.00458)	(0.00422)	(0.00145)	(0.0475)
Unempl. Risk	-0.272	-0.00358	-0.149*	-4.301**
	(0.200)	(0.146)	(0.0774)	(2.192)
Wage	0.204***	0.169***	0.0280***	-0.0118
	(0.0190)	(0.0224)	(0.00979)	(0.0372)
Controls	✓	✓	✓	✓
Observations	10987	10842	8647	11015
AR(1) in FD	0.000	0.000	0.000	
AR(2) in FD	0.150	0.215	0.199	
Hansen	0.451	0.847	0.287	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Variable and Symbol Definitions

Table 12: Variable and Symbol Definitions

Variable/Symbol	Definition
i	individual
t	year
ln and log	natural logarithm
Δ	difference between t and $t-1$
E	expectation operator
$\Phi()$	is the cumulative distribution function of a normal random variable
h_{it}	actual hours of work per week of individual (alternative definitions in Table 11: annual hours, paid hours, contracted hours)
h^*_{it}	desired hours of work per week
c_{it}	consumption
w^g_{it}	gross annual incomes from the primary and secondary jobs and from self-employment divided by hours worked in year t
w_{it}	net marginal wages calculated using the STSM
r_t	real interest rate
a_{it}	assets in period t
M_{it}	tax liability
n_{it}	other income including total individual income from labor earnings, asset flows, private retirement income and private transfers
$\alpha = 1-\theta$	speed of adjustment
μ_i	individual fixed effects
ρ	discount factor
$1/\gamma$	Frisch labor elasticity
ϑ	coefficient of relative risk aversion
b_{it}	taste shifter
υ_{it}	idiosyncratic taste shocks
e_{it}	approximation error
$\sigma_{w,it}$	measure for wage risk
$\mathrm{Pr}_{u,it}$	measure for unemployment risk
Ξ_{it}	vector of control variables including year dummies, years of education, indicator of East Germany, number of children under 18 in the individual, gender
E_i	currently employed individual
U^*_{it}	latent variable
Z^U_{it}	regressors for occupation, industry, region, education, age, age squared, age interacted with occupation and with education, marital status, unemployment experience, gender
W_{it}	regressors of heteroskedasticity function includes previous unemployment experience and years of education
σ^2_{it}	variance of probit model
ζ_{it}	normally distributed idiosyncratic shock
labin_{it}	labor income in period t
$\sigma^{\min}_{w,it}$	fixed minimum level of wage risk
$\hat{h}_{SR,it}$	short-run predicted hours with fixed minimum level of wage risk
$\hat{h}_{LR,it}$	long-run predicted hours with fixed minimum level of wage risk

Continued on next page

Variable	Definition
p_i	percentile ranking of individual i in observed distribution of hours
SR_{η_w}	short-run wage elasticity
$SR_{\eta_{\sigma_w}}$	short-run wage risk elasticity
LR_{η_w}	long-run wage elasticity
$LR_{\eta_{\sigma_w}}$	long-run wage risk elasticity