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Abstract

We quantify the importance of precautionary labor supply using data from the German Socio-Economic Panel (SOEP) for 2001-2012. We estimate dynamic labor supply equations augmented with a measure of wage risk. Our results show that married men choose about 2.5% of their hours of work or one week per year on average to shield against unpredictable wage shocks. This implies that about 26% of precautionary savings are due to precautionary labor supply. If self-employed faced the same wage risk as the median civil servant, their hours of work would reduce by 4%.

Keywords Wage Risk · Labor Supply · Precautionary Saving · Life Cycle · Dynamic Panel Data

JEL Classification D91 · J22 · C23

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1 Introduction

This study quantifies the importance of precautionary labor supply, defined as the difference between hours supplied in the presence of risk and hours under perfect foresight. Our findings show that married men choose about 2.5% of their hours of work or one week per year on average to shield against unpredictable wage shocks. This is an important part of the overall precautionary savings workers can accumulate by cutting consumption (see, e.g., Dynan 1993; Gourinchas and Parker 2002; Fuchs-Schündeln and Schündeln 2005) or working longer hours (Carroll and Kimball 2008). The current evidence for the importance of overall precautionary saving is mixed, but 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). In this study, we quantify the importance of wage risk, that is, the standard deviation of past hourly individual wages, for hours of work and examine how many additional hours of work result from the precautionary motive. This motive may exist if individuals consider their expectations about future wage shocks when deciding how much to work in a given period (Low 2005). Individuals with higher risk, for instance, the self-employed, would work more hours than those facing lower risks, even *before* shocks are realized to accumulate precautionary wealth.

Quantifying the relevance of precautionary labor supply is important, from both a theoretical and a policy perspective. Our contribution empirically corroborates the relevance of precautionary labor supply predicted in theoretical studies and provides parameters that rationalize this behavior. From a policy perspective, our study contributes to a better understanding of the effects of social security. Engen and Gruber (2001) showed that the social security system crowds out precautionary savings. Our study shows that this channel reduces the precautionary part of labor supply and quantifies this effect.

Some theoretical studies suggest that precautionary labor supply is important. Flodén (2006) demonstrates that higher wage risk increases first period labor supply in a two-period model with endogenous savings. Eaton and Rosen (1980) show that wage uncertainty increases labor supply under sufficiently high risk aversion. Pijoan-Mas (2006) shows that 15.2% of work hours are due to lack of insurance in an incomplete markets economy through a calibration exercise. However, this result is not directly comparable to Flodén's concept of precautionary labor supply, where individuals use additional hours of work to increase savings as an insurance device *before* the realization of wage risk. In this study, we focus on the latter concept of precautionary labor supply, that is, adjustments in work hours to address anticipated, but not yet realized, risks.

There is very little empirical research devoted to this issue, and the scarce evidence is mixed. Pistaferri (2003) finds that the effect of wage risk on labor supply agrees with the theory, but is negligible in practice. In contrast, Parker et al. (2005) show that the self-employed respond to greater earnings risk by working longer hours. Kuhn and Lozano (2008) find that work hours are longer in jobs with higher wage inequality, which could be evidence of precautionary labor supply. Recently, a vibrant debate was sparked by the paradox of toil (Eggertsson 2010), i.e. the observation that in recessions people work less even though they want to provide a few more hours a week due to the precautionary motive (Mulligan 2010; Eggertsson and Krugman 2012).

Our study contributes to this literature as the first to empirically quantify the amount of hours worked due to the precautionary motive. We connect insights on intertemporal labor supply choices from the seminal studies of Heckman and Macurdy (1980), MaCurdy (1981), and Blundell and Walker (1986)[1] with 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; Fuchs-Schündeln and Schündeln 2005; Fossen and Rostam-Afschar 2013).

We estimate the impact of wage risk on hours of work using German SOEP data for 2001 to 2012. Following Altonji (1986) and MaCurdy (1981), we focus our analysis on married men. Our measure for idiosyncratic wage risk is based on the variability of previous wage realizations, similar to Parker et al. (2005). To overcome potential endogeneity issues, we instrument wages and risk measures with lags and lagged labor income. Thus, our results provide causal evidence. To separate wage risk from other determinants of labor supply, we control for a rich set of variables including unemployment probability calculated similar to Carroll et al. (2003), as the predicted probability not to work in the next period. Since it might be difficult to adjust hours to their desired level instantaneously, we specify dynamic labor supply regressions to capture partial adjustment.

We find that workers choose about 2.5% 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 42 hours per week, precautionary labor supply amounts to about one week per year or in monetary terms, about 710 Euro per year, with a typical net wage rate of 13 Euro. If the self-employed faced the same wage risk as the median civil servant, their hours of work would drop by 4%. Our findings suggest that unemployment probability also plays a statistically significant role, but is quantitatively less important than wage risk.

To test whether our finding can indeed be interpreted as precautionary labor supply, we run

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

wealth regressions and replicate results from the literature on the size of precautionary savings. Assuming that half of these savings are precautionary, about one fourth results from precautionary labor supply and the rest from foregone consumption. In a two-period calibration exercise using our estimate for the Frisch labor elasticity (about 20%), we show that these results may be replicated with parameters that are in line with the literature.

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

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

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

where a_t represents assets, r_t the real interest rate, n_t non-labor income, and M_t tax liability, which depends on gross income and household characteristics. The gross wage rate w_t^g is stochastic.

Instantaneous utility takes the constant relative risk aversion (CRRA) form

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

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 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 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 that capture the second term on the right hand side in equation (1). In the empirical specification, X_{it} includes dummies for children of three age groups (younger than three, between three and five, or between six and 18) in the household, year dummies, years of education, tenure, a dummy for East Germany, age, and age squared in addition to a measure for unemployment probability $\Pr_{u,it}$ (see Subsection 3.2). The error term u_{it} contains e_{it} and a measure of wage risk, which we proxy with the term $\sigma_{w,it}$. Wage risk is measured as the within standard deviation of the idiosyncratic log wages from the previous five years (see Subsection 3.1. With these terms, the augmented labor supply equation is

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

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

The immediate adjustment labor supply equation is misspecified if individuals cannot adjust their hours of work immediately, for example, because hours of work are negotiated centrally for many occupations in Germany or because of the ”paradox of toil” (Eggertsson 2010). To allow for this possibility, we specify a partial adjustment model. Denote the *desired* labor supply by $\ln h^*_{it}$:

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

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

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

θ may be interpreted as the speed of adjustment. This speed might be determined by costs to immediately adjust the labor supply to desired hours or habit persistence (see, e.g., Brown 1952). Replace (5) in (4) to obtain the partial adjustment labor supply specification as in, for example, Baltagi et al. (2005):

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

[2]For a slightly different derivation that incorporates wage variance into the labor supply equation, see Pistaferri (2003).

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. Taking the first differences of equation (6), we obtain our empirical labor supply equation:

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

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

3 Empirical Strategy

3.1 Measurement of Wage Risk

We use data from the Socio-Economic Panel (SOEP) described in Subsection 3.4 to construct measures for both gross and marginal net wage risk. We calculate gross wages by dividing gross labor income by hours of work (see Subsection 3.4 for details). While we focus on net wages, we show results with gross wages as a robustness test. We calculate marginal net wage rates by scaling the gross wage y_{it}/h_{it} with the marginal net-of-tax rate:

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

that is, we increase each person's annual labor income y_{it} marginally.[3] We calculate net income $NetInc$ using the microsimulation model STSM. Jessen et al. (2015) present a comprehensive overview of marginal tax rates for different households (for more information, see Steiner et al. (2012)).

To obtain measures of wage risk we detrend, in a first step, log gross wage growth with a regression on age, its square, education, and interactions of these variables to avoid variations due to predictable wage growth, following, for instance, Hryshko (2012). In a second step, we obtain the sample standard deviation of the detrended log wage for each person for rolling sample windows of the previous 5 years similar to Parker et al. (2005).[4] Hence, our risk measure uses only the variation within individuals. The wage risk measure is given by

[3] We set $\Delta y_{it} = 2000$ Euro, which implies an increase in labor income of about 40 Euro per week.

[4] We use the remaining observed past wages for missing observations.

$$\sigma_{w,it} = \frac{1}{4} \sum_{j=t-6}^{t-1} \sqrt{(\tilde{w}_j - \bar{\tilde{w}}_j)^2},$$

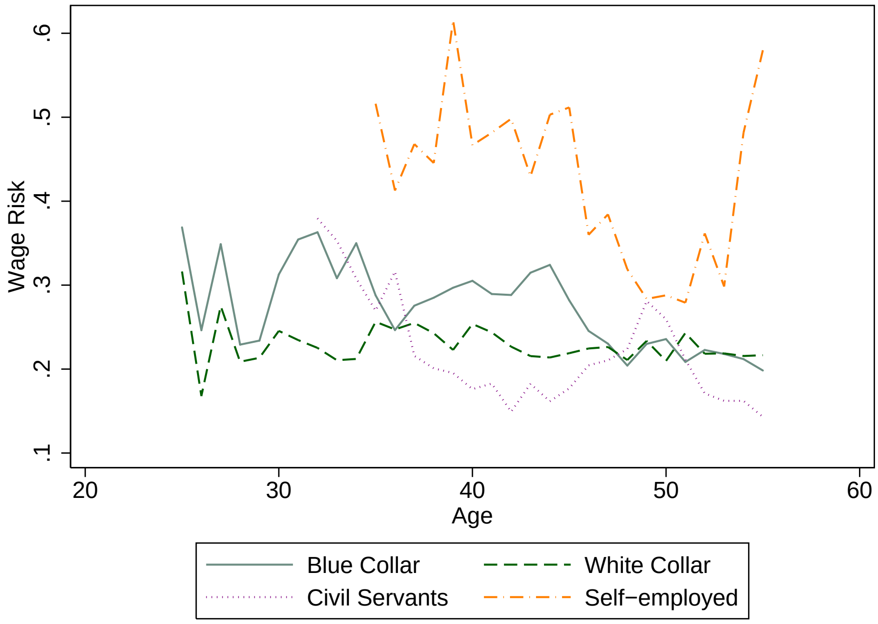
where $\tilde{w}_j$ denotes the detrended (net or gross) wage. The idea behind this measure is that workers use past variations in idiosyncratic wages to form expectations about future risk. Therefore, we may treat this measure as exogenous at the moment of the labor supply decision. We denote this measure 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 provide robustness tests with different risk measures, such as without detrending, subjective risk measures, or other household income risk in the Appendix in Table A5.

We divide our sample into blue collar workers, white collar workers, civil servants, and self-employed. Since we are mainly interested in decisions during work life at ages where occupational changes are rare, we leave extending our model to incorporate occupational choice to future research. This does not impair our results because we eliminate person-specific fixed effects and our risk measure is based on within-variation of wages. Figure 1 shows how the average net wage risk evolves over the life cycle for each subgroup. Only age-occupation combinations with more than 15 observations are displayed, thus the trajectory for self-employed starts at age 35. As expected, the hourly wages of self-employed workers are more volatile over the entire life cycle than those of employees. Blue and white collar workers have similar levels of wage risks. For most age groups, the average net wage risk of civil servants is slightly lower than those of blue collar and white collar workers.

3.2 Measurement of Unemployment Probability

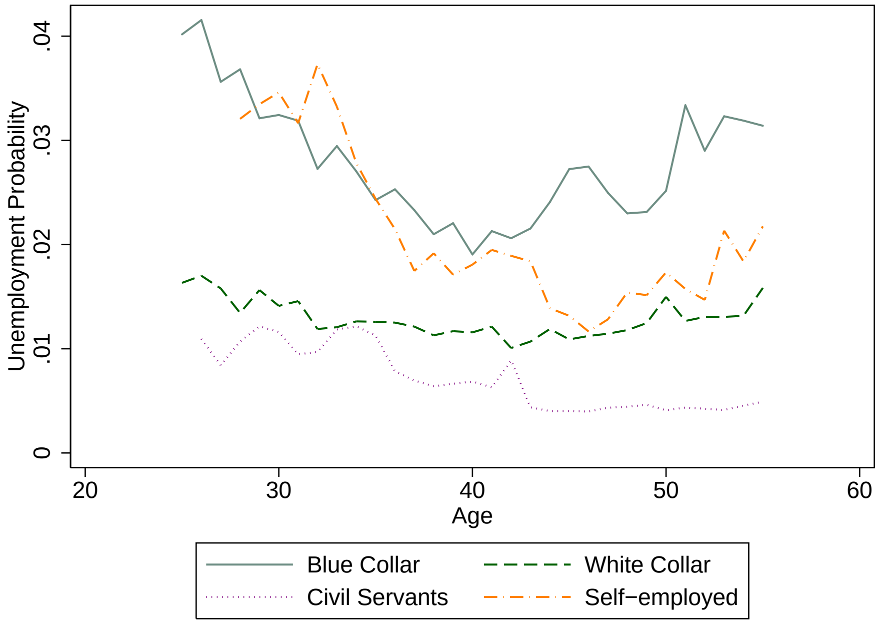
The control variable unemployment probability $\Pr_{U,it}$ is estimated similarly as in Carroll et al. (2003). We use a heteroskedastic probit model to estimate the probability of unemployment in the following year conditional on regressors for occupation, industry, region, education, age, age squared, age interacted with occupation, and with education, marital status, unemployment experience, and gender. The vector of regressors of the heteroskedasticity function includes previous unemployment experience and years of education.

Figure 1: Average Net Wage Risk over the Life Cycle



Note: Standard deviation of marginal net wages in past five years for currently working married men.

Figure 2: Average Unemployment Probability over the Life Cycle



Note: Predicted probability of unemployment next year for currently working married men.

This predicted probability $\Pr_{U,it}$ is then used as a regressor in our hours of work regressions.[5] Note that we exploit the panel structure of the SOEP to estimate the conditional probability of unemployment in the future rather than simply the unconditional probability of current unemployment. $\Pr_{U,it}$ can be thought of as a rational expectation of the odds of a currently working individual not to be working next year.

Figure 2 displays how the average unemployment probability evolves over the life cycle for the 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 probability, followed by white collar workers. For most parts of the life cycle, blue collar workers face the highest average unemployment probability.

3.3 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 the excluded instrument (Anderson-Hsiao estimator). In an alternative specification, we exploit additional moment conditions as suggested by Holtz-Eakin et al. (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 imposing additional restrictions on the initial values of the data generating process and using lagged levels and lagged differences as instruments improves the efficiency of the estimates. We also present the results from this estimator, called the system GMM (SYS-GMM). Following Roodman (2009), we collapse the matrix of instruments.

[5] For currently working individual i, we assume a latent variable $U^*_{it} = Z^U_{it}\alpha_U + \zeta_{it}$ such that $U^*_{it} > 0$ if the person will not be working in the following year and $U^*_{it} \leq 0$ otherwise. We assume ζ_{it} is a normally distributed idiosyncratic shock that is uncorrelated with Z^U_{it}, a row vector of observable characteristics for individual i at time t. 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. The dependent variable is an indicator that takes on a value of 1 if individual i works in year t and does not work in year $t+1$, and takes on a value of 0 if individual i works in both periods.

Second, marginal net wage rates may be endogenous for two reasons: First, measurement error in hours leads to downward denominator bias in the coefficient of wage rate since the hourly wage is calculated by dividing labor income by the dependent variable hours of work (cf. Altonji 1986; Keane 2011). Second, 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 during the current period labor supply choices and uncorrelated with the measurement error in current period hours.

3.4 Data

Our study uses data from the SOEP (version 30), a representative annual panel survey in Germany. Wagner et al. (2007) provide a detailed description of the data. We use observations from 2001-2012 and focus on men because the extensive margin plays an important role in women's labor supply decisions. Extending our model in this direction is an interesting avenue for future research. The sample is restricted to prime age (older than 25 and younger than 56) married men working at least 20 hours to allow comparisons with the canonical labor supply literature, for example, Altonji (1986) and MaCurdy (1981).[6] Further, we drop persons who indicated having received social welfare payments. We restrict our sample to individuals working between 20 and 80 hours per week. In total, we observe 10,987 data points from 2,488 persons. Table A1 in the Appendix summarizes the number of observations lost due to each sample selection.

Table 1 provides weighted summary statistics of the most important variables, including wage risk and unemployment probability measures. In the first row we report the average hours worked per week, about 42 in our sample. Hourly wages average 23 Euro, with average marginal net wages of 13 Euro.[7] To calculate hours of work and hourly wages, we construct weekly paid hours of work following Euwals (2005).[8] The general aim is to account for differences in compensation for overtime hours. We use paid hours because an increase in these translates directly into an increase

[6]Including unmarried men yields very similar results, available upon request.

[7]Hourly wages are constructed by dividing gross monthly labor incomes by paid hours of work. This and other monetary variables are converted to 2010 prices using the consumer price index provided by the Federal Statistical Office. Labor earnings include wages and salaries from all employment including training, self-employment income, and bonuses, overtime, and profit-sharing.

[8]Individual i may work according to one of two paid overtime rules or_{it} at time t. This is because the data provides information only on whether overtime was (a) fully paid, (b) fully compensated with time off, (c) partly paid, partly compensated with time off, or (d) not compensated at all. $I(or_{it} = a)$ is an indicator function, in this case indicating

Table 1: Summary Statistics

	Unit	Mean	Std. Dev.	Min	Max	N
Labor Supply						
Weekly Hours Worked	(h)	41.78	6.85	20	80	10,987
Wages and Incomes						
Hourly Gross Wage	(Euro)	22.62	10.15	2.27	98.06	10,987
Hourly Marginal Net Wage	(Euro)	13.07	6.33	1.04	57.67	10,987
Monthly Gross Labor Income	(Euro)	3,896.83	1,972.09	319	27,000	10,987
Monthly Net Labor Income	(Euro)	2,554.75	1,202.22	150	12,072	10,987
Wage and Unemployment Probability						
Gross Wage Risk	(ln Euro)	0.192	0.195	0	3.539	10,987
Marginal Net Wage Risk	(ln Euro)	0.249	0.224	0	3.354	10,987
Unemployment Probability	(%)	1.1	1.7	0	21.7	10,987
Demographics and Characteristics						
Age	(a)	43.9	7	25	55	10,987
Years of Education	(a)	12.9	2.7	7	18	10,987
Work Experience	(a)	22.3	7.9	2	41.2	10,987
Children younger than 3 years	(%)	9.0	28.6	0	100	10,987
Children between 3 and 6 years	(%)	14.2	34.9	0	100	10,987
Children between 7 and 18 years	(%)	48.5	50	0	100	10,987
East Germany	(%)	14.0	34.7	0	100	10987
Type of Work						
Self-Employed	(%)	6.5	24.7	0	100	10,987
Blue Collar	(%)	32.7	46.9	0	100	10,987
White Collar	(%)	48.2	50	0	100	10,987
Civil Servant	(%)	12.6	33.1	0	100	10,987
One-Digit International Standard Classification of Occupations (ISCO)						
Managers	(%)	10.6	30.8	0	100	10,987
Professionals	(%)	21.9	41.3	0	100	10,987
Technicians	(%)	21.1	40.8	0	100	10,987
Clerks	(%)	7.8	26.7	0	100	10,987
Service and Sales	(%)	4.6	20.8	0	100	10,987
Craftsmen	(%)	20.3	40.2	0	100	10,987
Operatives	(%)	9.7	29.6	0	100	10,987
Unskilled	(%)	4.1	19.9	0	100	10,987

Notes: Data from SOEP (version 30). Sample of married prime-age males; 2001-2012.

in income. Robustness tests using different measures of hours supplied are reported in Table A4. The last three variables in Table 1 show that our sample has 6.5% self-employed workers, about 32.7% blue collar workers, and about 48% white collar workers. Self-employed workers include freelance professionals and other self-employed persons. Blue collar workers include untrained and trained workers. White collar workers are employees with simple tasks, untrained and trained employees with simple tasks, qualified and highly qualified professionals, and managerial staff.

4 Results

4.1 Impact of Wage Risk on Weekly Hours of Work

Table 2 presents the results of the augmented labor supply equation for different estimators, where the dependent variable is log paid hours of work.[9] Standard errors are robust and clustered at the individual level. Columns 1 and 2 show the results for the immediate adjustment specification, column 3 for the specification (3) while columns 4–6 show results for the preferred dynamic specification (7).[10] The first column displays results for the pooled OLS. The coefficient of net wage is significantly negative, which is not in line with standard theoretical predictions and likely to be a result of the denominator bias described in Subsection 3.3. The main coefficient of interest is the one associated with wage risk. The coefficient of 0.021 indicates that an increase in wage risk by one standard deviation would increase labor supply by 2.1%. The coefficient on unemployment probability is very small and not statistically significant.

Column 2 shows results for the pooled 2SLS estimator[11], 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 and the coefficient of wage risk remains significantly positive with a point estimate of 0.028. The unemployment probability becomes significant and the point estimate of 0.016 implies that an increase in unemployment probability by one standard deviation translates into 1.6% more hours worked. Column 3 displays the results obtained with the first difference

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that overtime rule (a) applies. Therefore, we can approximate paid hours of work as $h_{it} = hc_{it} + I(or_{it} = a)(ht_{it} - hc_{it}) + 0.5I(or_{it} = c)(ht_{it} - hc_{it})$, where hc_{it} are contracted hours of work and ht_{it} are actual hours of work.

[9] Table A4 in the Appendix shows the results for alternative definitions of hours of work.

[10] Table A2 in the Appendix shows the equivalent table using gross wages instead of marginal net wages.

[11] We estimate it using the ivreg2 package (Baum et al. 2016).

estimator (FD-IV) with the equivalent instrument for net wages. The wage risk coefficient drops slightly but remains significantly positive.

The partial adjustment specification results appear in columns 4–6 with the Anderson-Hsiao estimator displayed in column 4 and the results for the Difference and System GMM estimators[12] displayed in columns 5 and 6, respectively. The immediate adjustment specification is rejected with all three estimators with point estimates of lagged hours of work between 0.12 and 0.16. For all three dynamic estimators, the coefficients of wage risk and unemployment probability are statistically significant. The magnitude of these effects is similar across all dynamic specifications and close to the results of the immediate adjustment specifications. The coefficient of marginal net wage is significant only for the system GMM estimator, implying a short run elasticity of $SR_{\eta_w} = 0.175$ and a long run elasticity of $LR_{\eta_w} = 0.20$. For the difference and system GMM estimators, autocorrelation and Hansen tests appear below the estimates. The null hypothesis of no autocorrelation of second order cannot be rejected and the Hansen overidentification test does not indicate any invalidity in the instruments.

[12] We estimate them using the xtabond2 package (Roodman 2009).

Table 2: Labor Supply Regressions with Alternative Instrumentation Strategies

	OLS	2SLS	FD-IV	Anderson-Hsiao	DIFF-GMM	SYS-GMM
Lag of Hours Worked				0.160***	0.153***	0.123***
				(0.042)	(0.041)	(0.037)
Net Wage Risk	0.021***	0.028***	0.009*	0.009*	0.009*	0.023***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)
Unempl. Prob.	0.002	0.016***	0.012**	0.011**	0.011**	0.012***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
Net Wage	-0.058***	0.148***	-0.071*	-0.058	-0.058	0.175***
	(0.011)	(0.021)	(0.039)	(0.042)	(0.038)	(0.019)
Controls	✓	✓	✓	✓	✓	✓
Instruments	—	labinc$_{it-1}$	Δlabinc$_{it-1}$	$\ln h_{it-2}$, Δlabinc$_{it-1}$	$\ln h_{it-2}, \ldots, \ln h_{it-13}$, collapsed, Δlabinc$_{it-1}$	$\ln h_{it-2}, \ldots, \ln h_{it-13}$, $\Delta \ln h_{it-2}, \ldots, \Delta \ln h_{it-13}$, collapsed, Δlabinc$_{it-1}$
Observations	10,987	10,821	8,031	7,989	8,112	10,755
AR(1) in FD					0.000	0.000
AR(2) in FD					0.883	0.212
Hansen					0.289	0.186

Notes: Columns 1-2: Estimation of an immediate adjustment labor supply equation.
Column 3: Estimation of equation (3).
Columns 4-6: Estimation of equation (7) using different estimators.
Robust standard errors clustered at the individual level 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 resulting distribution of hours if all individuals faced the same small wage risk. We construct this simulated counterfactual $\hat{h}_{it}$ from the prediction of equation (7) with minimum sample wage risk $\sigma_{w,it}^{\min}$. We use the estimates obtained with the System GMM estimator. We then 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 rank p_i of individual i in the actual observed distribution of hours of work (vertical axis) and h_i indicates the actual hours of work (horizontal axis). 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 $\sigma_{w,it}^{\min}$. 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 $\sigma_{w,it}^{\min}$.[13]

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

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 the reduction in the number of hours 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 the reduction in the number of hours of work in the long-run if wage risk were reduced to the

[13] Infinite horizon models with patient consumers, that is, whose time preference rate is equal to or less than the interest rate, may describe the behavior of dynasties or central planners but are empirically not relevant for individual consumers because patient consumers accumulate assets indefinitely such that income and thus precautionary labor supply becomes irrelevant as capital income increasingly finances consumption (Deaton 1991, 1992). Therefore, consumers must be impatient to desire to borrow. With borrowing constraints, precautionary labor supply may be empirically relevant. Carroll (1997) shows how infinite-horizon models with relevant precautionary saving behavior compare to finite-horizon models and outdated certainty equivalence versions where labor supply is exogenous.

Figure 3: Reduction in Hours of Work

Notes: Small circles indicate the percentile rank of individual i in the actual observed distribution of hours of work (vertical axis) and the actual hours of work (horizontal axis) in 2011. Triangles maintain the percentile ranking from the observed distribution and indicate the simulated short-run *value of the hours of work when* $\sigma_{w,it}$ *is set to* $\sigma_{w,it}^{min}$*. Plus symbols denote the respective long-run hours of work when* $\sigma_{w,it}$ *is set to* $\sigma_{w,it}^{min}$*.*

Table 3: Percentage Reduction for Different Occupations

	Short-Run		Long-Run	
	Perfect Foresight	Civil Servants	Perfect Foresight	Civil Servants
Self-Employed	4.88	3.57	5.53	4.04
Blue Collar	2.09	0.74	2.38	0.84
White Collar	1.98	0.64	2.26	0.72
Civil Servants	1.92	0.58	2.19	0.65
All	2.19	0.85	2.49	0.96

Notes: Simulated percentage reduction in hours of work when reducing wage risk to the sample minimum (perfect foresight) or the median risk faced by civil servants.

minimum level. The horizontal difference between simulated points in the long- and short-run indicates how much of the adjustment in hours would occur as an immediate reaction to the wage risk reduction.

Table 3 reports the labor supply reduction 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 median wage risk of civil servants (columns 2 and 4). Civil servants have a below average wage risk and are generally regarded as a group with relatively low uncertainty (Fuchs-Schündeln and Schündeln 2005). In our sample, hours of work would reduce by 2.49% in the long run if wage risk were reduced to the sample minimum. Keep in mind that this is a ceteris paribus exercise neglecting general equilibrium effects. 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 of 42 weekly paid hours of work in our sample, precautionary labor supply amounts to 1.05 hours per week on average. This effect is economically important, particularly for the self-employed, a group, which faces average wage risks substantially above the sample mean.

If wage risk were reduced instead to the average wage risk of civil servants, labor supply would decrease on average by 0.96% in the long run. For the self-employed, the long-run labor supply reduction would still amount to 4%. If the wage risk of all civil servants were reduced to its median, civil servants' labor supply would decrease by 0.65%.[14]

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

4.3 Results by Occupations

The key results in Table 3 differ across occupational groups due to differences in wage risk. To quantify this heterogeneity across groups, we present the results of our preferred specification across the groups introduced above and other occupational classifications. Table 4 provides separate results for different occupational groups using the system GMM estimator with the same instruments as in Table 2.[15] As before, the risk measures are normalized by one standard deviation; however, this time not by the overall, but the sub-sample specific standard deviation. The point estimate of the wage risk coefficient is positive and statistically significant for self-employed, white-collar, and blue-collar workers, but not statistically different from zero for civil servants. The point estimate is largest for self-employed workers (0.035) and much smaller for white-collar (0.010) and blue-collar workers (0.007), suggesting the important role of precautionary labor supply for the self-employed. The coefficient on the lag of paid hours worked is not statistically significant for the self-employed and civil servants, which makes intuitive sense. These two groups are not as severely constrained in their hours choices as regular employees. Blue-collar workers (0.228) are more constrained than white-collar workers (0.123). The coefficient of net wage is positive and statistically significant for all groups.

The coefficient of net wage, that is, the Frisch elasticity, is positive and significant for all groups. It is higher for civil servants than for other occupational groups. This makes intuitive sense, as the Frisch elasticity is given by $1/\gamma$ and a large ”risk aversion with respect to leisure” implies a high Frisch elasticity. Fuchs-Schündeln and Schündeln (2005) document self-selection into public service by individuals with high risk aversion. As in the estimation using the entire sample, we cannot reject the null hypothesis of no autocorrelation of second order. The Hansen test indicates that the instrument may be invalid only for blue-collar workers.

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 one-digit ISCO group is composed of several of the occupational classifications we used above, that is, some managers are self-employed, some not. The null hypothesis that wage risk does not affect labor supply is rejected for managers, professionals, technicians, craftsmen, and operatives. The coefficient of net wage is significantly positive for all but service workers and operatives. Generally, both the coefficients of net wage risk and net wage are of similar magnitude as

[15] Results obtained using gross wages instead of net wages appear in Table A3 in the Appendix.

Table 4: System GMM Labor Supply Regressions for Occupational Groups

	Self-Employed	White Collar	Blue Collar	Civil Servant
Lag of Hours Worked	0.122	0.123***	0.228***	0.037
	(0.099)	(0.048)	(0.055)	(0.130)
Net Wage Risk	0.035***	0.010***	0.007**	-0.007
	(0.012)	(0.003)	(0.003)	(0.007)
Unempl. Prob.	-0.012	0.005	0.010***	-0.001
	(0.014)	(0.004)	(0.004)	(0.005)
Net Wage	0.127***	0.131***	0.059***	0.253***
	(0.046)	(0.020)	(0.022)	(0.096)
Controls	✓	✓	✓	✓
Observations	860	5,561	2,927	1,407
AR(1) in FD	0.000	0.000	0.000	0.001
AR(2) in FD	0.723	0.859	0.478	0.273
Hansen	0.186	0.359	0.024	0.356

Notes: Estimation of equation (7) using the SYS-GMM as in column 6, Table 2.
Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

those obtained in the estimation using the main sample. None of the specification tests rejects the validity of the estimator.

Table 5: System GMM Labor Supply Regressions for ISCO Groups

	Managers	Professionals	Technicians	Clerks	Service and Sales	Craftsmen	Operatives	Unskilled
Lag of Hours Worked	0.159*	0.111	-0.050	0.435***	0.012	0.051	0.349***	0.371
	(0.091)	(0.077)	(0.105)	(0.140)	(0.123)	(0.066)	(0.083)	(0.249)
Net Wage Risk	0.024***	0.027***	0.021***	0.005	0.011	0.020***	0.033***	0.015
	(0.008)	(0.007)	(0.007)	(0.003)	(0.010)	(0.006)	(0.012)	(0.018)
Unempl. Prob.	0.020**	0.007	0.007	-0.008*	0.001	0.019***	0.011*	0.015*
	(0.009)	(0.006)	(0.007)	(0.004)	(0.010)	(0.007)	(0.006)	(0.008)
Net Wage	0.186***	0.305***	0.170***	0.045*	0.051	0.181***	0.089	0.180**
	(0.058)	(0.052)	(0.040)	(0.027)	(0.059)	(0.042)	(0.063)	(0.078)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,300	2,960	2,165	797	394	1,953	862	324
AR(1) in FD	0.000	0.000	0.000	0.000	0.086	0.000	0.000	0.014
AR2inFD	0.557	0.235	0.699	0.718	0.443	0.226	0.110	0.755
Hansen	0.844	0.140	0.393	0.348	0.447	0.166	0.171	0.192

Notes: Estimation of equation (7) using the SYS-GMM as in column 6, Table 2.
Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Does Precautionary Labor Supply Show Up in Savings?

In this subsection, we test whether our results for precautionary labor supply appear in precautionary saving. Additional hours worked can only be interpreted as precautionary labor supply if they lead to more savings. Therefore, precautionary savings must be influenced by the measure of wage risk that also affects labor supply. We test this restriction by regressing log net wealth on wage risk, unemployment probability, log of disposable household income, and the same control variables as in Subsection 4.1.[16]

Table 6 presents estimates obtained using the first-difference estimator (FD) 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 9%. A comparison between actual net wealth and counterfactual net wealth at minimum wage risk shows that precautionary wealth amounts to 22,216 Euro and 22,312 Euro on average with fixed effects and first differences, respectively. This amount covers average consumption expenditures for about 9 months. However, the standard errors are too large to obtain statistical significance.

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

In our sample, average monthly savings are about 450 Euro. 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 an average of about 42 hours per week and earn an hourly marginal net wage of about 13 Euro. With our estimate of the share of precautionary weekly hours of 2.5% (Table 3), precautionary savings due to precautionary labor supply are 59 Euro per month or 26% of precautionary savings. If only 20% of total savings are due to precaution, precautionary labor supply amounts to 66% of precautionary savings.

[16] 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 the following, we use the five wealth implicates imputed by the SOEP according to Rubin's rule (Little and Rubin 1987; Rubin 1987).

Table 6: Precautionary Savings with Imputed Net Wealth

	FD	Fixed Effects
Wage Risk	0.094	0.091
	(0.089)	(0.091)
Unempl. Prob.	0.438	0.436
	(0.281)	(0.283)
Log Disposable Income	0.301	0.309
	(0.312)	(0.313)
Controls	✓	✓
Observations	515	1,997

Notes: Net wealth is observed in survey years 2002, 2007, and 2012. For our sample (see Table A1), the mean over the 5 implications of the weighted mean of this variable is 231,024 2010 Euro, the median is 168,662 2010 Euro, and the standard deviation is 286,840 2010 Euro.

Robust standard errors clustered at the individual level in parentheses.

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

4.5 A Calibration Exercise

The result that 26% of precautionary savings is due to precautionary labor supply is consistent with a simple simulation exercise of a two-period version of our model in Section 2.[17] We set certain wages in the first period to 13 Euro, the hourly marginal net wage in the sample (Table 1). In the second period, wage realizations of 8 Euro or 18 Euro are possible with equal probability. We take the Frisch labor supply elasticity $1/\gamma$ from the main results in Subsection 4.1 as 0.20. We calibrate the coefficient of relative risk aversion ϑ and the parameter b to match the observed mean weekly hours of work (Table 1). The respective values of the parameters are -1.67, and 2.5×10^{-12}.[18] 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 for the optimal solution under both uncertainty and certainty algebraically. Under certainty, where the second period wage is 13 Euro, the first and second period labor supply are the same, $h_1 = h_2 = 42.42$ hours per week and savings $s = 0$ Euro. Under uncertainty, the first period labor supply is $h_1 = 43.60$ weekly hours, the second period labor supply $h_2 = 41.62$ weekly

[17] We assume that second period labor supply is chosen before wages are known.

[18] Chetty (2006) shows that commonly estimated labor supply elasticities are in line with $\vartheta > -2$.

hours, and savings $s = 59.11$ Euro. The difference in first period labor supply under uncertainty and certainty gives precautionary labor supply per week. In this simulation, it is 1.19 weekly hours, which is in line with the results in Section 4.2. With an hourly wage of 13 Euro, the sample average, this implies that 26.08% of precautionary savings are due to precautionary labor supply. In this simulation, 73.92% are due to cuts in consumption.

5 Summary and Conclusions

We quantify the importance of wage risk to explain the hours of work of married men. The analysis is based on German Socio-Economic Panel (SOEP) data for 2001 to 2012. We find that workers choose slightly more than an hour per week to shield against unpredictable wage shocks. Workers adjust hours of work with changes in idiosyncratic wage risk. These effects are statistically significant for various occupations, but not for civil servants, which is in line with previous studies. We observe the largest absolute and relative effects of wage risk for the self-employed.

Labor supply adjustments to wage risk can only be interpreted as *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 savings. 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 due to the precautionary motive, we show that about 26% of precautionary savings are due to precautionary labor supply.

To verify that our estimated results are in line with theoretical predictions, we calibrate a simple two period model. Using realistic parameters of the utility function, including our estimate of the Frisch labor supply elasticity, we replicate our empirical finding that about a quarter of precautionary savings are due to precautionary labor supply.

Precautionary labor supply is economically important, particularly for the self-employed, a group that faces average wage risks substantially above the sample mean. This group works 5.53% of their hours because of the precautionary motive. If all workers faced the same risk as the median civil servant, hours worked would decrease on average by 1% in the long run.

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6 Appendix

A Sample Restrictions

Table A1: Sample Restrictions

Full sample: 416,241 person years	*Eliminated*	*Remaining*
Incomplete interviews	9,829	406,412
Drop if female	207,407	199,005
Drop if not married	55,457	143,548
Drop if younger than 26 or older than 55 in each year	86,223	57,325
Drop if in military or agriculture	2,155	55,170
Drop if transfer recipients	6,806	48,364
Drop if very low hours worked	495	47,869
Drop if unrealistic hours changes	115	47,754
Drop if unrealistic wage changes	670	47,084
Drop if without net wage or risk	36,097	10,987

B Results using Gross Wages

Table A2: Comparison of Specifications, Gross Wages

	OLS	2SLS	FD-IV	FD-IV	DIFF-GMM	SYS-GMM
Lag of Hours Worked				0.174***	0.171***	0.128***
				(0.044)	(0.039)	(0.037)
Gross Wage Risk	0.029***	0.033***	0.001	0.002	0.002	0.027***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)
Unempl. Prob.	-0.000	0.012**	0.008	0.009	0.004	0.009***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)	(0.003)
Gross Wage	-0.095***	0.142***	-0.003	0.006	0.011	0.175***
	(0.014)	(0.023)	(0.029)	(0.033)	(0.026)	(0.021)
Controls	✓	✓	✓	✓	✓	✓
Instruments	—	labinc_{it-1}	$\Delta\text{labinc}_{it-1}$	$\ln h_{it-2}$, $\Delta\text{labinc}_{it-1}$	$\ln h_{it-2},\dots,\ln h_{it-13}$, collapsed, $\Delta\text{labinc}_{it-1}$	$\ln h_{it-2},\dots,\ln h_{it-13}$, $\Delta\ln h_{it-2},\dots,\Delta\ln h_{it-13}$, collapsed, $\Delta\text{labinc}_{it-1}$
Observations	10,987	10,821	8,156	8,114	11,276	10,755
AR(1) in FD					0.000	0.000
AR(2) in FD					0.144	0.809
Hansen					0.396	0.141

Notes: Columns 1-2: Estimation of an immediate adjustment labor supply equation.
Column 3: Estimation of equation (3)
Columns 4-6: Estimation of equation (7) using different estimators.
Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Occupational Groups, System GMM, Gross Wages

	Self-Employed	White Collar	Blue Collar	Civil Servant
Log of Hours Worked	0.114	0.128***	0.230***	0.028
	(0.102)	(0.048)	(0.054)	(0.125)
Gross Wage Risk	0.032**	0.011***	0.005*	-0.008
	(0.013)	(0.003)	(0.003)	(0.007)
Unempl. Prob.	-0.012	0.004	0.011***	0.001
	(0.015)	(0.004)	(0.004)	(0.005)
Gross Wage	0.132**	0.139***	0.068**	0.206**
	(0.054)	(0.022)	(0.028)	(0.094)
Controls	✓	✓	✓	✓
Observations	860	5,561	2,927	1,407
AR(1) in FD	0.000	0.000	0.000	0.001
AR(2) in FD	0.947	0.488	0.429	0.330
Hansen	0.379	0.180	0.042	0.407

Notes: Estimation of equation (7) *using the SYS-GMM as in column 6, Table* 2.
Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Robustness of Results

Table A4 shows our preferred specification (System GMM) for four alternative dependent variables. *Annual hours* (column 1) refers to the SOEP-imputed annual hours of work. *Weekly hours*, another variable imputed by the SOEP, is the basis for our hours worked definition but without adjusting for paid overtime. Respondents are asked directly about *Contracted hours* and *Desired hours*. From a theoretical point of view, desired hours should not be constrained by a partial adjustment mechanism (cf. Euwals 2005); hence, we specify an immediate adjustment model for this specification.

Table A4: Alternative Hours Definitions

	Annual Hours	Weekly Hours	Contracted Hours	Desired Hours
Lag of Hours	0.117	0.108	0.204**	
	(0.0756)	(0.0697)	(0.0806)	
Wage Risk	0.0234***	0.0197***	-0.00140	-0.0323
	(0.00386)	(0.00356)	(0.00132)	(0.0450)
Unempl. Prob.	0.00850**	0.0123***	0.000458	-0.0563
	(0.00389)	(0.00364)	(0.00182)	(0.0350)
Wage	0.217***	0.215***	0.0320***	0.00563
	(0.0242)	(0.0233)	(0.00768)	(0.0379)
Controls	✓	✓	✓	✓
Observations	11,034	10,845	8,739	10,932
AR(1) in FD	0.000	0.000	0.000	0.000
AR(2) in FD	0.496	0.135	0.731	0.921
Hansen	0.414	0.481	0.942	0.792

Notes: Estimation of equation (7) using the SYS-GMM as in column 6, Table 2.
Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5 shows our preferred specification (System GMM), but with four different risk specifications. Column 1 shows the case with constructed risk measures, as before, but omitting the detrending of wages. This measure corresponds to the one used by Parker et al. (2005).[19] Columns 2 and 3 include indicators of subjective risk preference (Some Worries, Big Worries), column 4 includes the risk of additional household income as an additional control. This is constructed as for wage risk, but using net household income minus net labor income of the household head instead of the household head's wage.

Table A5: Alternative Risk Definitions

	No Detrending	Subj. Risk	Subj. & Wage Risk	Household Risk
Lag of Hours Worked	0.126***	0.202**	0.169***	0.126***
	(0.037)	(0.079)	(0.062)	(0.038)
Net Wage Risk	0.021***		0.020***	0.020**
	(0.003)		(0.005)	(0.009)
Unempl. Prob.	0.011***	0.006	0.007	0.011***
	(0.003)	(0.007)	(0.005)	(0.004)
Net Wage	0.177***	0.228***	0.196***	0.158***
	(0.019)	(0.040)	(0.029)	(0.052)
Some Worries		0.227	0.097	
		(0.209)	(0.147)	
Big Worries		0.550	0.308	
		(0.361)	(0.260)	
Net Household Risk				0.011
				(0.056)
Controls	✓	✓	✓	✓
Observations	10,755	10,736	10,736	10,527
AR(1) in FD	0.000	0.011	0.000	0.000
AR(2) in FD	0.929	0.674	0.505	0.291
Hansen	0.158	0.951	0.443	0.209

Notes: Estimation of equation (7) using the SYS-GMM as in column 6, Table 2.
Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[19] Variables used are the same as with detrending.

D Variable and Symbol Definitions

Table A6: 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 i (alternative definitions in Table A4: annual hours, paid hours, contracted hours)
h^*_{it}	desired hours of work per week
c_{it}	consumption
w^g_{it}	gross annual incomes from primary and secondary jobs and from self-employment divided by hours worked in year t
w_{it}	net marginal wages calculated using the STSM
$\tilde{w}_j$	detrended (net or gross) wage $j+t$ years ago
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
$\Pr_{u,it}$	measure for unemployment probability
Ξ_{it}	vector of control variables including year dummies, years of education, indicator of East Germany, number of children under 18 in the household, 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, and 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

Continued on next page

Variable	Definition
$\hat{h}_{LR,it}$	long-run predicted hours with fixed minimum level of wage risk
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

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