Biased Wage Expectations and Female Labor Supply
Working paper

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Abstract

We quantify the effects of biased wage expectations on female labor market outcomes. A wide sample of full-time and part-time employees report counterfactual predictions about their own wage trajectories in future full-time and part-time employment, revealing severe misperceptions. Actual wage growth occurs almost exclusively in full-time work whereas it is close to zero in part-time work, as we show with reduced-form regressions and in a structural life-cycle model. Subjective expectations, however, predict a mild difference in the opposite direction, with strong over-optimism about part time. We leverage the structural model to quantify how the employees' beliefs influence their labor supply and wages over the life cycle. The bias increases part-time employment strongly, induces flatter long-run wage profiles, and substantially affects two widely discussed policy reforms. The largest impact of the bias appears for college-educated women, consistent with the large difference between expected and realized wages observed for this group.

Key words: Returns to experience, Biased beliefs, Part-time work, Dynamic life-cycle models.

JEL classification: D63; H23; I24; I38; J22; J31.

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1 Introduction

We investigate the extent to which possible misperceptions about long-run wage prospects contribute to the empirical patterns in women's labor supply. The recent decades saw sizable increases in most OECD countries' female labor force participation, yet gender imbalances in the labor market persist.[1] Selection effects can rationalize many imbalances in the short run, but the dynamic effects of labor supply are harder to explain and raise additional issues (Goldin 2021). One important set of issues lies in the long-run consequences of entering part-time and flexible work arrangements, where women are overrepresented (Petrongolo 2004, Goldin 2014, Cortés & Pan 2019). While serving as a reconciliation tool between work and care responsibilities (Connolly & Gregory 2010), part-time work yields lower human capital accumulation and, in combination with differential promotions and pay raises, induces flatter long-run wage profiles (Gicheva 2013, Blundell et al. 2016). Careers with large wage growth appear almost exclusively in full-time employment, whereas part-time wage profiles are essentially flat.

This leads to the question whether employees, when choosing between full-time and part-time work, have correct expectations about the long-run implications of their choice. Even if they base their decision on sound empirical observations, they need to make a substantial volume of predictions: assessments of their possible earnings trajectories both in part-time and in full-time employment. While such counterfactual reasoning is standardly assumed in economic life-cycle models, a lower degree of real-life clairvoyance may lead to sub-optimal career choices. Indeed, many studies show that expectations held by members of the general population are often inaccurate, malleable, and influential for economic choices (Coibion & Gorodnichenko 2012, Das et al. 2022, Roth & Wohlfahrt 2020, Fuster et al. 2022). We thus measure women's expectations about their own earnings in both part-time and full-time employment scenarios, quantify the implications of these expectations for employment and lifetime earnings, and evaluate policies aiming to increase labor supply.

In our sample, which is designed to be representative of employed women in Germany, we observe realistic-but-somewhat-pessimistic expectations about full-time wage growth, judged by comparison with realized wages. In contrast, we observe strongly inflated expectations about wage growth in part-time work. The average subjective expectation is that an additional year of experience increases wages by about 1.5 percent per year, in full-time *and* in part-time employment. In actual fact, returns to part-time experience are close to zero, which we show in two ways: via reduced-form estimations that use a control function approach and via a structural life-cycle model. For full-time experience, we estimate returns at close to two percent per year. All of these estimates of realized returns confirm evidence from the UK by Blundell et al. (2016), while the findings on asymmetric expectation accuracy between full-time and part-time are novel in the literature, to our knowledge.

Considering heterogeneity in beliefs, we document relatively small differences in belief biases between subgroups, most notably between full-time and part-time workers. Almost irrespective of current employment status, the respondents fail to predict the large difference in wage growth between full-time work and part-time work. Current part-timers expect somewhat higher returns to part-time work, consistent with their employment choice. We also find that college-educated women underestimate life-cycle part-time penalties more than the less educated. Average expectations differ only mildly by education group, but the realized part-time penalty is highest for women with a college degree.

The structural model allows us to also assess the consequences of belief biases. Simulations of the model show that the bias translates into an increased propensity of part-time employment by about eight percentage points on average across the population of Germany's female employees. This result is produced by counterfactually imposing rational expectations in the model, and comparing its predictions to those that generate from the full model with biased beliefs. Interestingly, lower expected returns to part-time work experience would induce about

[1] In 2022, female employment rates averaged at 62 percent across OECD countries. In Germany, the country under study here, female employment rate reached 73 percent in 2022, compared to 59 percent in 2005 (OECD 2022).

half of the responding women to increase working hours to full-time and the other half to leave employment, thereby increasing both full-time employment and non-employment by about the same amount. However, there is noteworthy response heterogeneity. In particular, we find that employment effects are strongest for women with college education: Over the full life-cycle, de-biasing would reduce part-time employment of college-educated women by about 13 percentage points, while full-time employment would increase by about eight percentage points. Correspondingly, we find the strongest welfare effects of de-biasing for college educated women, whose lifetime income would increase by about three percent, on average.

Finally, we study policy reforms that aim to increase labor suppy (and welfare). The first is a tax reform that is widely discussed in Germany: abandoning joint assessment of married couples' taxes. The reform would increase most married women's work incentives. However, female labor supply is elastic and, as we show, depends on beliefs. Policy makers targeting an increase in female employment would therefore need to provide additional incentives for full-time work. The second reform is an increase in subsidies for child care (attempting to counteract the pattern that female labor-force participation drops strongly around the birth of the first child). Here, again, we find that the bias about long-run implications of working part-time mutes the labor supply effects of the reform.

To derive these results, we include tailored questions into the Innovation Sample of the German Socio-Economic Panel Study (SOEP-IS), a survey of private households that takes extensive measures for representativity of Germany's general population. The tailored questions ask each respondent about their own expected future wage growth in full-time and in part-time employment, using hypothetical scenarios in a within-subject design: we depict two counterfactual continuations of respondents' careers over the next ten years – working part-time, at 20 hours per week, or working full-time, at 40 hours per week.[2] The respondents report their expected one-year, two-year and ten-year wage growth for each of these hypothetical scenarios and we can thus measure, at the individual respondent level, the perceived difference in the returns to experience between full-time and part-time work.

To quantify the effects of a possible bias, we use two econometric strategies. First, we contrast the perceived returns to experience with estimates of the realized returns to experience, using a control function approach to address selection effects and endogeneity in observational data. For identification, we follow Blundell et al. (1998) and Attanasio et al. (2018), exploiting variation in the tax and transfer system over time to construct suitable instruments. The longitudinal data of the core sample from the German Socio-Economic Panel (SOEP) is a suitable source for estimating realized returns as an exact analogue to the perceived returns: it features an equivalent data environment to the SOEP-IS and includes cases of both hypothetical trajectories (part-time/full-time), with a suitably large set of socio-demographic variables that is common to both the SOEP core sample and the SOEP-IS. Second, we develop a life-cycle model of labor supply and consumption decisions similar to Blundell et al. (2016) and Adda et al. (2017) to estimate long-term wage trajectories together with dynamic employment choices. Such dynamic modeling is relevant for many reasons, not least because labor-supply choices are made repeatedly over time: they are subject to changing life circumstance, such as the presence of children in the household. In contrast to previously formulated dynamic models, we explicitly allow for biased beliefs about the returns to full-time and part-time work experience, thus letting the misperceptions affect employment decisions and the life-cycle wage process. For estimation, we use indirect inference and match moments from the SOEP core sample and the expectations elicited in the SOEP-IS. Both econometric techniques yield very similar results, allowing to leverage the model and quantify the effects of biased expectations and simulate policy reforms, as described above.[3]

[2]Schrenker (2022) studies the perceived effect of part-time work on current wages, whereas we analyze expectations about future wage growth.

[3]We can validate multiple results of the structural model using the control function estimates. Moreover, the structural model replicates reduced-form results from Geyer et al. (2015), who study the employment effect of a sizable reform of parental leave regulation that strongly affected financial incentives for mothers.

Our paper is related to the literature on expectations held by the general population about various environments, for example stock markets (see, e.g., Dominitz & Manski 2007, Hurd et al. 2011, Drerup et al. 2017, Breunig et al. 2021b), housing markets (Armona et al. 2019, Kuchler & Zafar 2019), and human capital formation and labor markets (Arcidiacono et al. 2020, Boneva et al. 2021, Delavande & Zafar 2019, Jäger et al. 2022, Wiswall & Zafar 2021). We add to it our emphasis on biased long-run wage expectations that we examine as a possible driver for human capital accumulation. Previous studies have analyzed the effects of part-time work perceptions on current wages (Schrenker 2022, Stevens et al. 2004) but not their effects on long-run outcomes.[4]

In deviating from rational dynamic optimization, our paper also relates to non-standard models of labor-market behavior by, among others, Fang & Silverman (2009) and Chan (2017) who allow for time-inconsistent preferences in the form of hyperbolic-discounting, and Schneider (2020), who incorporates biased beliefs about labor market frictions.[5] We add to these approaches our quantification of the effect of misperceptions, including a novel investigation of the misperceptions' interactions with policy reforms that aim at incentivizing full-time work. The life-cycle model builds on previous structural models by Adda et al. (2017), Blundell et al. (2016), who have previously quantified the evolution of dynamic part-time wage penalties over the life span.[6]

Finally, our paper contributes to a large literature studying female labor supply and part-time employment (e.g. Francesconi 2002, Fernández-Kranz & Rodríguez-Planas 2011, Paul 2016, Cortés & Pan 2019). Part-time employment in OECD countries is a largely female phenomenon, which has been explained by social norms (Boneva et al. 2021), preferences (Adda et al. 2017), financial incentives (Bick & Fuchs-Schündeln 2017), and fertility timing (Wasserman 2019). Overall, a striking pattern in the literature on labor supply is that gender is a dominant predictor not only for lower work hours, but also for lower hourly wages (Manning & Petrongolo 2008, Goldin 2014, Cortés & Pan 2019), and lower long-run returns to experience for part-time work (Blundell et al. 2016, Adda et al. 2017, Schneider 2020). This suggests that entering part-time work has, in many cases, severe consequences. Yet, misperceptions have not been previously examined as a driver of women's career choices, to our knowledge. Given that information about one's short-term earnings opportunities, including the part-time wage, is readily available at the time of choosing a part-time job, we regard it as natural to ask whether the long-run implications are equally well understood. We find that the answer is negative for the large majority of women and that this misperception corresponds to a sizable portion of part-time labor supply.

The remainder of this paper is organized as follows. Section 2 describes the data environment and sample. Section 3 presents our novel evidence on wage expectations and estimates the returns to experience as they are perceived by the respondents. In Section 4, we estimate the realized returns to experience, juxtaposing it with its perceived analogues. Section 5 presents the structural model, Section 6 reports and discusses the results of its estimation, and Section 7 presents the policy simulations. Section 8 concludes.

2 Data

This Section presents the data samples. We use two large sub-samples from the German Socio-Economic Panel, described in Section 2.1.[7] Section 2.2 outlines the main sample restrictions, while additional sample restrictions that are required for the estimation of the structural model appear in Appendix Appendix I.2. Appendix

[4]For detailed surveys of the fast-growing literature on expectations data, see Kosar & O'Dea (2022) and Mueller & Spinnewijn (2022) as well as other surveys that appeared in the same collection. An overview of long-run economic expectations of German households, including some of the data used in this paper, is given in Breunig et al. (2021).

[5]Similar approaches have been used in the context of labor search models, e.g., DellaVigna & Paserman (2005), Spinnewijn (2015) or DellaVigna et al. (2017).

[6]Methodically, our paper also builds on previous work by using variation in the tax and transfer system as exclusion restrictions to model selection into part-time and full-time employment, thereby accounting for the endogeneity of wages and working hours (Attanasio et al. 2018, Arellano & Bonhomme 2017, Blundell et al. 2016, Costa Dias et al. 2020).

[7]We gratefully acknowledge access to the SOEP data (SOEP 2018) and the SOEP Innovation Sample data (SOEP-IS 2019) provided by the Research Data Center of the Socio-Economic Panel (FDZ SOEP).

Appendix I.1 contains a detailed definition of all relevant variables.

2.1 The German Socio-Economic Panel (SOEP)

The SOEP consists of two separate but related annual surveys, the SOEP core sample and the Innovation Sample SOEP-IS. Both the SOEP core sample and the SOEP-IS are longitudinal surveys that are carefully designed to be representative of German households (Goebel et al. 2019). The SOEP-IS was established in 2011 and supplements the SOEP core sample by enabling the inclusion of new research questions. Recruitment method, survey design and administration are almost identical. Appendix Table SWA.1 provides evidence that the selected samples of the SOEP-IS and the SOEP core sample are representative of the same population. Both also include a wide and common set of socio-demographic variables.

We introduce tailored questions, described in Section 3, into the SOEP-IS in order to measure the perceived returns to full-time and part-time work. The SOEP core sample is far larger than the SOEP-IS, allowing us to estimate the corresponding realized returns to experience. Also, the SOEP core sample has a long panel dimension that we exploit to estimate the realized returns in connection with part-time and full-time labor supply choices. Specifically, the core SOEP contains detailed labor market trajectories including information about wages, employment, household formation and further demographic characteristics over time. These year-respondent level variables can also be integrated into our structural model of labor supply over the life cycle.

2.2 Sample Restrictions

The tailored expectation questions appear in subsets of three SOEP-IS waves, during the period 2016-2018. For the estimation of realized wage growth, we use the SOEP core sample from 1992-2018 in the reduced-form analyses, and we restrict the observation period to 2007-2018 for the structural model.[8] We restrict the age range to women between 22 and 60 to study wage growth after completed education and before retirement. Our estimation samples contain all women after completed education and training, except civil servants, military officials, pensioners and individuals in community service. The SOEP-IS sample is further restricted to women who are in regular full-time or part-time employment. In contrast, when estimating realized wage growth from the SOEP core sample (in reduced-form regressions and in the structural model), we include non-employed women to account for potential selection effects. Women in marginal employment ('Mini-Jobs') are, however, always excluded.[9]

Our restricted SOEP core sample for the period 1992-2018 contains N=92,198 women-year observations, with approximately 3,400 women per period, and the 2007-2018 sample for the structural analysis contains 67,526 women-year observations with about 5,600 women per period. In the restricted SOEP-IS sample, we use N=473 women-year observations obtained during 2016-2018.

3 Expected Returns to Full-Time and Part-Time Work Experience

Section 3.1 introduces the survey instruments used to measure the respondents' beliefs and Section 3.2 summarizes the responses descriptively. Section 3.3 presents the empirical strategy for estimating the perceived returns to experience, with the corresponding estimates appearing in Section 3.4.

[8] This restriction keeps the income taxation laws constant throughout the sample period, allowing the use of a single tax function.

[9] We do not survey wage expectations for women in marginal employment, who constitute approximately six percent of women in the sample.

3.1 Survey Instruments

The 21 survey questions that we include in the SOEP-IS questionnaire implement a within-person belief elicitation about counterfactual scenarios, asking each respondent to predict their own future wage growth in full-time and in part-time employment. Measuring all expectations regardless of a worker's current employment status allows us to identify the perceived difference in the returns to experience between full- and part-time work at the individual respondent level, conditional on current and past individual-specific characteristics and choices. Its interpretation is that of a set of potential outcomes, as perceived by the worker herself.

In more detail, respondents report their perceived returns to experience in three steps. In the first step, they report their expected earnings in one year, in two years and in ten years, holding constant their current state of self-reported employment (full-time or part-time). In the second step, full-time working respondents are asked to consider a hypothetical switch to working part-time at 20 hours, whereas part-time workers are asked to consider switching to a full-time position at 40 hours, *ceteris paribus*, and report their expected current earnings in the hypothetical scenario. Third and finally, respondents are asked to imagine remaining in the hypothetical scenario for one year, two years and ten years, and report expected future earnings in this scenario.

In addition to providing point estimates of their earnings expectations in Euro amounts, respondents report probabilistic answers to all questions. In them, they indicate how probable they assess a deviation from the point estimate by more than 20 percent, separately in each direction. Appendix Appendix II contains a description of the exact wording of the survey questions and provides results based on probabilistic-answer formats (Table SWA.2).

3.2 Perceived Wage Growth in Full- and Part-Time Employment

Evidence of expected wage growth profiles is presented in Figure 1, separately for full-time and part-time working female employees. Table 1 shows sample averages of expected wage growth across all women and for additional subgroups.

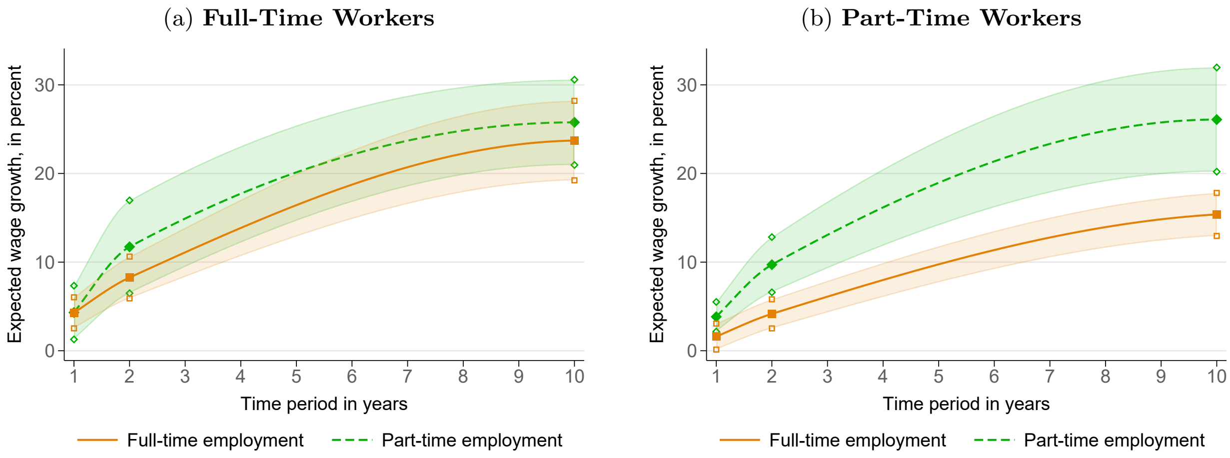


Figure 1: Expected Wage Growth in Full-Time and in Part-Time Employment

Notes: The plots show expected growth in gross hourly wages when working part-time at 20 hours or full-time at 40 hours over the next years, separately for full-time workers (Panel a, N=109) and part-time workers (Panel b, N=130). Markers indicate average reported point estimates, with 95% confidence bands. Markers are connected by a fitted smooth piece-wise interpolating function. Used observations are from a balanced panel of women who gave valid responses for all eight questions asking for point estimates (SOEP-IS 2016-2018).

Expected wage increases denote changes in percent relative to wages in the year of the survey response. The depicted expectation averages show a clear pattern: respondents expect no part-time penalty in earnings growth, in that the expected hourly wage from working part-time remains close to that of full-time. Differentiating between the two plots in the figure, we see that full-time working women expect wage growth to be the almost exactly the same in full- and part-time employment. Part-time workers even expect a stronger part-time wage growth. This pattern is surprising at first glance, but it is consistent with many possible selections of self-justifications of the part-time choice (Bertrand & Mullainathan 2001). Overall, women expect similar earnings growth in part-time and in full-time employment in the short run, and expect higher wages in part-time relative to full-time employment in the medium and long run, i.e. after two and ten years. On average, reported 1-year-out expectations show perceived earnings increases by three percent in part-time employment and four percent in full-time employment (Table 1, first versus second column); after two years, respondents expect wages to increase by six percent in full-time work and 11 percent in part-time work; after ten years, the average increase in expected earnings is 19 percent in full-time work and 25 percent in part-time work.

Across the different subgroups that we consider, no-one expects a part-time penalty in earnings growth. However, relevant differences appear by level of education, age and region. Higher educated women, younger women, and women living in Western Germany expect earnings to grow faster than others. For example, the average 10-year-out expectation for women with high education level is 23 percent (full-time) and 30 percent (part-time), compared to only 19 percent and 20 percent for women with low education level; women younger than 35 years expect 28 percent and 34 percent wage increases, while women older than 45 years expect only an increase of 15 percent and 18 percent, respectively. These group-specific patterns are in line with empirical findings about the realized returns to experience (Breunig et al. 2021, Blundell et al. 2016). The fact that inter-group differences follow the empirical patterns of realized returns is evidence of a relatively high level of sophistication in respondents' expectations; this observation makes it even more remarkable that no subgroup of the population predicts a part-time wage penalty.

Table 1: Expected Wage Growth in Part-Time and Full-Time Employment (in %)

	1 year			2 year			10 year		
	Full-time	Part-time	p-val	Full-time	Part-time	p-val	Full-time	Part-time	p-val
All Females	2.82	4.05	0.23	6.03	10.63	0.01	19.18	25.94	0.00
Employment status									
Full-Time	4.28	4.31	0.98	8.26	11.73	0.24	23.71	25.77	0.54
Part-Time	1.60	3.84	0.05	4.16	9.71	0.00	15.38	26.08	0.00
Education									
Low	2.22	3.24	0.72	5.48	7.88	0.53	18.95	20.14	0.83
Medium	2.05	3.14	0.29	5.30	8.45	0.04	17.60	25.23	0.01
High	5.11	6.81	0.56	8.19	17.48	0.07	23.49	30.00	0.16
Income									
Low (<P25)	2.09	5.78	0.14	6.36	13.10	0.08	19.84	32.86	0.10
Medium (P25-P75)	3.21	3.40	0.85	6.31	9.07	0.08	20.20	25.53	0.05
High (>P75)	2.59	4.05	0.58	5.25	11.86	0.15	16.66	21.56	0.19
Age									
$<$ 35 years	5.60	4.35	0.41	10.76	14.60	0.21	27.67	34.33	0.24
35-45 years	1.87	6.56	0.07	4.55	14.71	0.02	16.58	28.23	0.01
$>$ 45 years	1.46	2.16	0.59	3.63	5.03	0.31	14.81	18.36	0.10
Region									
East	1.85	5.03	0.08	6.16	9.30	0.20	19.52	24.86	0.21
West	3.05	3.82	0.52	6.00	10.95	0.01	19.10	26.20	0.01

Notes: SOEP-IS (2016-2018). Balanced panel of women with valid responses for all 8 expectation questions (N=239). We report expected growth in hourly wages (in percent), calculated in relation to observed hourly wage in the base period. We use the reported working hour to calculate hourly wages in the observed employment state. For the hypothetical scenario we use the working hours as defined in the questionnaire, 40 hours per week in full-time and 20 hours per week in part-time. The p-values (p-val) refer to the significance of the mean difference between full-time and part-time.

3.3 Estimation of the Perceived Returns to Experience

We use the elicited expectations to describe the expected wage process. Specifically, we estimate the perceived returns to experience in part-time and in full-time employment as expected by the survey respondents, according to Equation (1):

$$log(Ew_{it}) = \alpha + \zeta log(E_{it}^{Full}) + \beta log(E_{it}^{Part}) + \mu_i + \epsilon_{itp} \tag{1}$$

where Ew_{it} denotes the expected gross hourly wage that individual i expects to earn at time t.[10] The experience variables, one for part-time employment, E_{it}^{Part} and one for full-time employment, E_{it}^{Full}, are specified according to the horizon of the expectation questions, taking the values zero (for today's earnings), one year, two years and ten years, $t \in \{0, 1, 2, 10\}$. In addition, we include an individual-specific fixed effect in our main specification, denoted by μ_i.[11] We use a log specification of the experience terms to capture potential non-linear effects of experience. In a set of sensitivity checks, we show that the main findings are robust to various functional forms including a linear experience specification (see Section 3.4).

3.4 Perceived Returns to Full- and Part-Time Work Experience

Table 2 presents the estimated experience coefficients, in different specifications with and without individual-specific fixed effects. The estimations in Column 1 and 2 only use the information of expected future wages, whereas the estimations in Column 3 and 4 also include information about observed and counterfactual wages in the current period (t=0). In addition, the Table provides test statistics indicating whether the experience terms in part-time and full-time employment are significantly different.

Table 2: Expected Annual Returns to Full-Time and Part-Time Experience

	(1)	(2)	(3)	(4)
Log experience in full-time	0.079***	0.084***	0.065***	0.075***
	(0.006)	(0.009)	(0.005)	(0.008)
Log experience in part-time	0.092***	0.083***	0.089***	0.086***
	(0.008)	(0.011)	(0.006)	(0.009)
Difference part-/full-time	0.013*	0.001	0.024***	0.012
	(0.007)	(0.011)	(0.006)	(0.009)
N	1,926	1,745	2,722	2,473
Estimation	FE	POLS	FE	POLS
Incl. t=0	no	no	yes	yes

Notes: SOEP Innovation Sample (2016-2018). Unbalanced panel of women with valid response to at least one expectation question. Dep. Var. = Expected log gross hourly wage. Standard errors clustered at the person-level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. FE = Fixed Effects, POLS = Pooled OLS. Regressions include controls for current employment status, age, education, tenure, years of unemployment, region, migrational background, firm size, public sector employment, marital status and number of children.

In line with the descriptive evidence, the regression results show that individuals expect similar returns to experience both in part-time employment and in full-time employment. Depending on the specification and the sample, we find an expected wage elasticity with respect to full-time experience of 0.065-0.085. Considering the specification in Column 1, the wage elasticity amounts to 0.08, i.e. an increase in full-time experience

[10] In the regressions we focus on hourly wages rather than earnings for better comparability to the analysis of realized wages. Hourly wages are constructed based on information about (expected) monthly earnings, current agreed contractual working hours and the hours thresholds specified in the survey instruments, 20 hours for part-time and 40 hours for full-time employment, respectively.

[11] In an alternative specification, we estimate Equation (1) by OLS. In this specification, we omit the individual fixed effects, but alternatively add a vector of individual-specific covariates that are constant over t but may vary across respondents i. Covariates include an indicator for current employment status, age, education, tenure, years of unemployment, region, migrational background, firm size, public sector employment, marital status and number of children.

by ten percent increases expected wages by about 0.8 percent. For part-time experience, the expected wage elasticity varies between 0.08-0.09. Importantly, in all specifications, the difference in the returns to experience in part-time work and full-time work is small; in specifications where it is significantly different from zero, the effect is higher for the returns to part-time work.[12]

We also consider the results for different subgroups by education (Columns 2-4 in Table 3). The results show the same pattern as for the full sample (Column 1). For none of the education groups we find a statistically significant difference in the expected returns to part-time and full-time experience; i.e., no subgroup expects a penalty in part-time experience. In Table SWA.4, we extend the heterogeneity analysis and repeatedly confirm the same pattern for different subgroups.

Table 3: Expected Annual Returns to Full-Time and Part-Time Experience by Education

	Total (1)	Low education (2)	Medium education (3)	High education (4)
Log experience in full-time	0.079***	0.082***	0.078***	0.080***
	(0.006)	(0.013)	(0.007)	(0.015)
Log experience in part-time	0.092***	0.083***	0.089***	0.104***
	(0.008)	(0.011)	(0.010)	(0.013)
Difference part-/full-time	0.013*	0.001	0.011	0.024*
	(0.007)	(0.013)	(0.010)	(0.012)
N	1,926	182	1,281	463

Notes: SOEP Innovation Sample (2016-2018). Unbalanced panel. Dep. Var. = Expected log gross hourly wage. Fixed Effects regressions excluding t=0. Standard errors clustered at the person-level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Robustness checks In Appendix Appendix II.4, we provide evidence that our main result is robust to various changes in the specification. We show that the results of the specification with linear experience effects are very similar. The returns of an additional year of part-time and full-time experience vary between 1.4-1.9 percent and the difference between the two experience effects is not significant at the five percent confidence level. Moreover, the findings do not change when adjusting wage expectations for price increases and focusing on real instead of nominal wages. Finally, we show that the results are similar when eliciting beliefs in terms of hourly wages instead of monthly earnings.

4 Realized Returns to Experience

To quantify the bias of the expected returns to experience, we contrast the expected returns to experience in part-time and in full-time work with the realized returns, which we estimate based on longitudinal SOEP data. First, we provide descriptive evidence about employment and wage trajectories in part-time and full-time employment over the working life. Then, we turn to the econometric analysis and estimate the realized returns to experience accounting for potential selection effects and endogeneity of experience.

4.1 Female Employment and Wages

The first two panels of Figure 2 show the importance of part-time work for female employment, documenting the shift from non-employment to part-time employment since the 1990s. Non-employment rates of women have been strongly decreasing over the last 30 years. At the same time, we see a steady increase in part-time employment, explaining most of the increase in overall employment. The full-time employment rates slightly fluctuate over time, but, overall, the share of full-time working women did not change very much between 1990 and 2018. The level and increase in part-time employment over time does not strongly differ by education:

[12]In contrast to Boneva et al. (2021) who show that individuals predict earnings losses for part-time working mothers, we document that women expect similar earnings growth in part-time and full-time employment when asked about their own wage trajectories. One potential explanation would be that women are generally aware of part-time career penalties, but, in line with overconfidence, underestimate the dynamic effect of part-time work when asked about their own earnings paths.

In Panel (b), we show that the part-time shares for women with low, medium and high education increase at similar rates.

The central driver for female employment are children. In Panel (c), we compare part-time rates between women with and without children by education groups. The pattern is very clear cut: for mothers, part-time rates are higher among all education groups. The sizable and persistent effect of children on part-time work is also documented in Panel (d). Here we compare part-time shares for mothers before and after giving birth. Part-time shares before giving birth to the youngest child are moderate. Around birth of the youngest child, overall employment decreases. Part-time rates then strongly increase with the age of the child, remaining fairly high even when the youngest child reaches age 15.

In Panels (e) and (f), we compare the life-cycle wage profiles of women in part-time and full-time employment overall and by level of education. Wages increase with education as one would expect, with very flat wage-age profiles among low educated women. The age profile for the high educated is steep in the beginning of the career and increases moderately after the age of 40.[13] Both overall and within education groups, wage profiles are lower among part-time working women, especially for women with low and medium education. The figures thus provide first suggestive evidence for a part-time experience penalty. However, in order to quantify the effect of accumulated experience in full-time and part-time employment on wages, it is necessary to control for selection effects, endogeneity of experience, individual effects and differences between the groups.

4.2 Returns to Experience: Reduced Form Evidence

To estimate the realized returns to education, we specify a wage equation similar to Equation 1, in which the actual years of experience in part-time and in full-time work differentially affect hourly wages:

$$log\omega_{it} = \alpha + \zeta log E_{it}^{Full} + \beta log E_{it}^{Part} + X_{it}\gamma + \mu_i + \epsilon_{it}, \tag{2}$$

where ω_{it} measures the hourly wage. E_{it}^{Full}, and E_{it}^{Part} capture years in experience in full-time and part-time work respectively, μ_i is an unobservable individual fixed effect and ϵ_{it} an i.i.d error term. Given the log transformation of experience, we add one year of experience to all women, which allows us to include also women with no experience in either full-time or part-time employment. To provide a causal interpretation of the returns to part-time and full-time experience, it is necessary to account for endogeneity of accumulated experience and selection into part-time and full-time employment. In addition to accounting for individual fixed effects, we therefore use a control function approach similar to Blundell et al. (1998), and use the variation in the tax and transfer system over a long time period as instruments. Haan & Prowse (2017) show that multiple reforms of the tax and transfer system in Germany introduce time-specific variation in marginal tax rates and the net household income that vary by pre-tax earnings. In our analysis, we follow Costa Dias et al. (2020) and simulate the net household income out-of work, in part-time employment and in full-time employment. We then use the simulated incomes in the three employment states, as well as the number and age of children present in the household, as instruments to construct control functions.[14]

Formally, we augment Equation 2 and introduce control functions to account for selection into employment (λ^e), selection into full-time work (λ^h), and endogeneity of experience in part-time employment (λ^f) and in full-time employment (λ^p).

$$log\omega_{it} = \alpha + \zeta log E_{it}^{Full} + \beta log E_{it}^{Part} + X_{it}\gamma + \mu_i + \lambda^e + \lambda^h + \lambda^f + \lambda^p + \epsilon_{it}, \tag{3}$$

[13] Blundell et al. (2016) report a very similar pattern for the UK.

[14] For a similar procedure for Germany, see Hammer (2020).

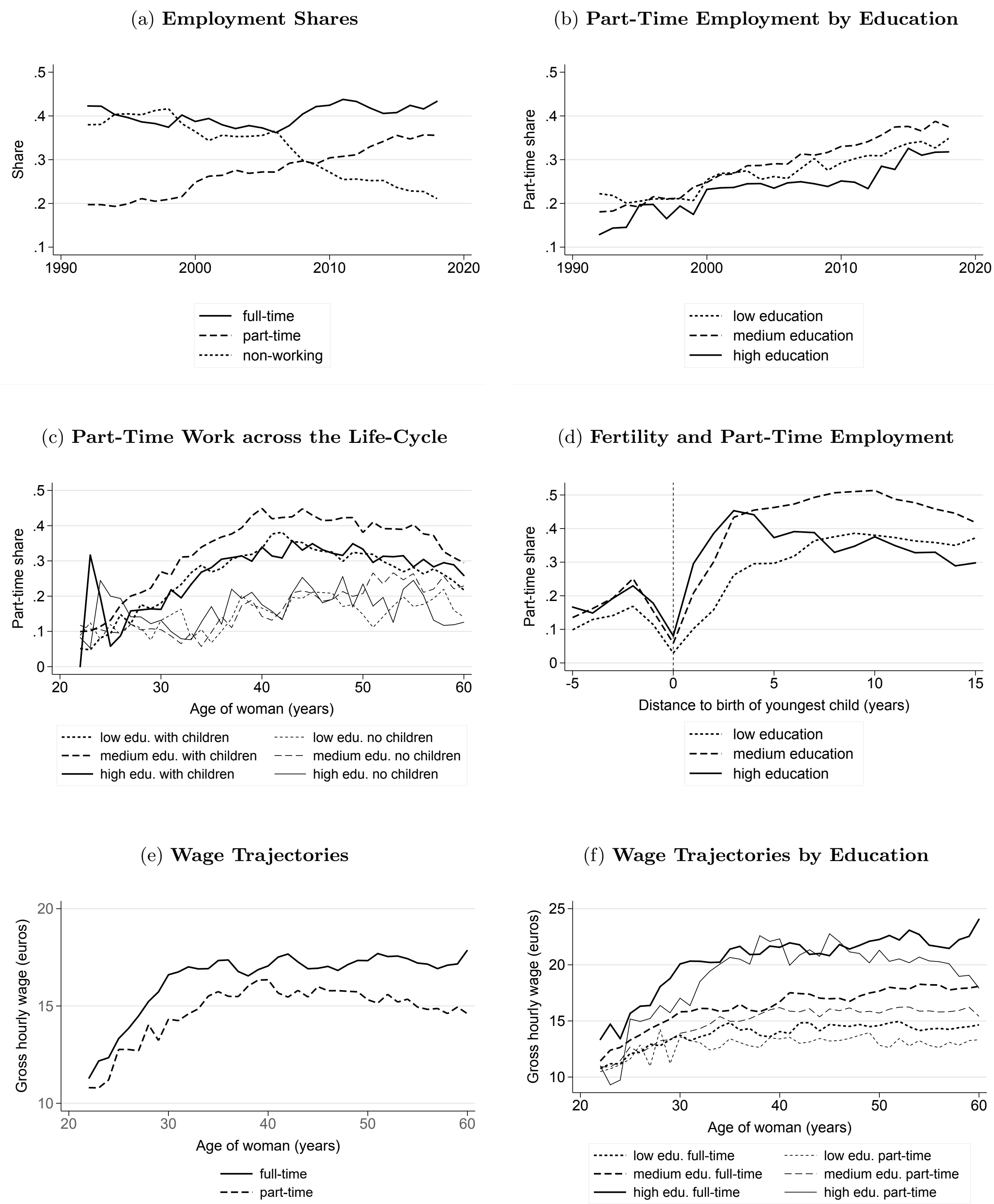


Figure 2: Employment and Wages of German Women 1992-2018

Notes: Source: SOEP V. 35 (2018), Own calculations.

We estimate the wage equations separately for women with low, medium and high education.

Table 4: Estimated Returns to Full-Time and Part-Time Experience

	Low Education		Medium Education		High Education	
	(1)	(2)	(3)	(4)	(5)	(6)
Log experience in full-time	0.100***	0.096***	0.176***	0.173***	0.221***	0.204***
	(0.012)	(0.013)	(0.007)	(0.008)	(0.013)	(0.014)
Log experience in part-time	0.041***	0.038***	0.036***	0.039***	0.051***	0.054***
	(0.009)	(0.012)	(0.005)	(0.007)	(0.009)	(0.014)
e		-0.038*		-0.035*		-0.083**
		(0.022)		(0.019)		(0.033)
h		-0.010		-0.019		-0.002
		(0.022)		(0.013)		(0.023)
f		0.003		0.003		0.018***
		(0.003)		(0.003)		(0.005)
pt		0.003		0.002		0.015***
		(0.003)		(0.003)		(0.006)
Constant	2.234***	2.280***	2.249***	2.280***	2.378***	2.427***
	(0.029)	(0.034)	(0.019)	(0.021)	(0.033)	(0.037)
Prob > F ($lnE^{Full} = lnE^{Part}$)	0.0003	0.0046	0.0000	0.0000	0.0000	0.0000
N	23,696	23,696	48,534	48,534	19,968	19,968

Notes: SOEP v35. All estimations include a fixed effect and an indicator for living in Eastern Germany. The control functions account for selection into employment (λ^e), selection into full-time employment (λ^h), and endogeneity of experience in full-time employment (λ^f) and in part-time employment (λ^p). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table 4, we present estimates of the wage equation using fixed effects regressions with and without control functions. The specifications of the control functions and the estimation results are relegated to Appendix Appendix III.

We find similar patterns in all specifications and for all education groups: The realized returns to full-time experience are always considerably larger than the realized returns to part-time experience. Depending on the specification, the experience effect (elasticity) for full-time work lies between 0.09-0.1 for low educated women, i.e. an increase in the years of experience of ten percent increases wages by 0.9-1 percent. For medium educated women, the elasticity is slightly higher (0.17-0.18), and for highly educated women it is between 0.2-0.22. In contrast, the estimated returns to part-time work experience are smaller than 0.06 for all education groups and in all specifications. F-tests on the equality of the returns to experience in full-time and part-time employment are rejected in all specifications. Thus, we can clearly document a penalty to part-time experience in the realized wage trajectories. For low educated women, the difference is smaller but still statistically significant. This is consistent with the finding that returns to full-time experience are lower for low educated individuals and therefore more similar to the returns to part-time experience, see e.g. Blundell et al. (2016). In Appendix Appendix III, we show that our results are robust to changes to the functional form of the wage specification: Returns to full-time experience are also significantly higher than returns to part-time experience when including an indicator for part-time work in the current period and in a specification with linear and quadratic experience effects.

Overall, our results are consistent with the previous literature which finds only minor or no returns to part time experience and a sizable part-time penalty in human capital accumulation for the UK (Blundell et al. 2016, Costa Dias et al. 2020) and for Germany (Hammer 2020).[15]

Comparing estimates of the realized returns with women's expectations (Table 2), we observe a strong beliefs-bias in the perceived returns to experience. While realized and expected returns to full-time work experience are comparable in size, expectations about the returns to part-time experience strongly diverge from realized returns to part-time work. This result is the motivation and the basis for the subsequent structural analysis, in which we further explore and quantify the implications of biased expectations. Specifically, we build a structural model to quantify the implications of biased beliefs for employment behavior and life time earnings. In addition, we use the model to evaluate the implications of various policy reforms when individuals have biased beliefs.

5 Structural Analysis

To analyze and to quantify the implications of biased beliefs about the returns to experience in part-time and full-time work, we develop and estimate a life-cycle model of female employment. First, we use the model to quantify the effects of biased beliefs on employment and life-time earnings. We then leverage the structural model and evaluate the implications of biased beliefs when evaluating policy reforms. Specifically, we look at two reforms that increase incentives for full-time employment: i) replacing joint taxation with individual taxation, and ii) subsidizing child care costs.

5.1 Overview of the Model

The structural model is similar to the life-cycle models of female labor supply developed in e.g. Blundell et al. (2016) or Adda et al. (2017). One key novelty in contrast to the previous literature is that we do not impose rational expectations about human capital accumulation in the wage processes. Instead, we explicitly allow for potentially biased beliefs about the returns to experience, with the standard assumption of rational expectations being nested within this framework. The life-cycle model includes the following main features: i) a choice of female labor supply which includes non-employment, part-time and full-time employment, ii) a wage process with differential human capital accumulation in part-time and full-time employment, iii) a description of the relevant elements of the tax and transfer system including child care costs, and iv) exogenous processes of household formation and male life-time earnings. We estimate all processes separately by education (low, medium and high education) and model choices of women from the moment they complete education and enter the labor market. As experience accumulation in the late working career has only minor effects on wages, we define the last period $\bar{t}$ as age 50. Therefore, we can abstract from early retirement rules and disability programs which become relevant after that age.

Time is discrete, and a period corresponds to a year. As in Blundell et al. (2016), we model household formation, fertility, and the earnings process of the male partner outside the structural model. Female employment and consumption decisions depend on these processes and the counterfactual policies account for the heterogeneity in these dimensions.[16] In the following, we describe the central elements of the structural model in more detail. The exogenous processes are presented in Appendix Appendix IV.

5.2 Utility and Value Function

Each period, a household chooses consumption (c_t) and female working hours (h_t) according to the following utility function:

$$u(c_t, h_t; \theta, Z_t) = \frac{(c_t/n_t)^{\mu}}{\mu} exp\{U(h_t, \theta, Z_t)\} \tag{4}$$

[15] Costa Dias et al. (2020) and Hammer (2020) focus on wage growth and account for human capital depreciation when analyzing returns to experience.

[16] We abstract from savings decisions of the household, thus the period income determines consumption.

with

$$U(h_t, \theta, Z_t) = \begin{cases} 0, & \text{if } h_t = N, \\ \theta_{(h_t)} + Z_t'\beta(h_t), & \text{if } h_t = P \text{ or } F, \end{cases} \tag{5}$$

where $\beta(h_t) = \beta_F + \beta_P \cdot \mathbf{1}\ (h_t = P)$. The vector Z summarises other characteristics that we consider relevant determinants of the preferences for work. In particular, we control for the presence of children and the age of the youngest child. The parameter vector β_F corresponds to the preference for full-time work associated with the presence of children, generally, and the additional effect when a child is aged 0-2, 3-5, and 6-10. The parameter β_P corresponds to the change in the experienced disutility of work when the woman works part-time instead of full-time. In the above flow utility (4), c_t/n_t represents consumption per adult equivalent, while μ governs risk aversion and inter-temporal substitution. We set μ to -0.56. The vector $\theta = (\theta_p, \theta_f)$ contains the persistent unobserved heterogeneity in part-time and full-time employment in the form of discrete mass points. Each woman is one of k numbers of types, such that the individual type is associated with a specific preference for full-time work θ_F, and a specific level of preference for part-time work θ_P.

Households maximize the sum of expected life-time utilities, which can be expressed in the following value function

$$V_t(X_t) = \max_{\{c_\tau, h_\tau\}_{\tau=t,\ldots,\bar{t}}} E\{\sum_{\tau=t}^{\tau=\bar{t}} \delta^\tau u(c_t, h_t; \theta, Z_t)|X_t\}, \tag{6}$$

We assume exponential discounting and set the discount factor δ to 0.98. Agents who are low and medium educated enter the model when aged 22, while highly educated agents enter the model aged 24 (for more details, see Appendix Appendix IV.1).

Households maximize the value function to the following budget constraint

$$c_t = h_t w_t + \tilde{w}_t - T(h_t, X_t) + CB - CC$$

Consumption is determined by labor earnings, the tax and transfer system (T), child benefits (CB) and child care costs (CC). Labor earnings of the household consist of the woman's own labor earnings, $h_t w_t$, and the exogenous labor income of the partner, $\tilde{w}_t$, if present in the household. Contributions to and from the tax and transfer system depend on household earnings and the structure of the household, and child benefits and child care costs are determined by the number and the age of the children, and vary between part-time and full-time employment. For the estimation of the structural model, we focus on the period 2007-2018. During that time period, the general structure of the tax and transfer system was only slightly changed.[17] In Appendix Appendix V, we provide a detailed description about the rules of the tax and transfer system and how the rules are implemented in the structural model.

5.3 Wages

The realized wages earned in the labor market are determined by the following process:

$$ln\, w_{st} = \gamma_{s,0} + \gamma_{s,F}\, ln(e_F + 1) + \gamma_{s,P}\, ln(e_P + 1) + \xi_{st} \tag{7}$$

[17] A major tax reform was implemented between 2000 and 2004 and labor market reforms took place between 2003-2005. The reform of parental leave benefits (the introduction of the "Elterngeld") was introduced in 2007, see e.g. Geyer et al. (2015).

The process of log hourly wages $ln\, w_{st}$ varies by level of education (s) and depends on the individual experience stock in full- and part-time employment, e_P respectively e_F. We note that the specification allows for a differential effect of part-time and full-time experience on human capital accumulation. ξ_{st} is a transitory wage shock.

5.4 Subjective Expectations

We extend the life-cycle model by introducing a parameter that captures a potential bias in expectations about the rate of experience accumulation in part-time employment relative to full-time employment. We set the expected contribution of the part-time experience stock ($\bar{\gamma}_{s,P}$) to

$$\bar{\gamma}_{s,P} = \alpha_s \cdot \gamma_{s,P} \tag{8}$$

where α governs the bias in beliefs. The standard assumption of rational expectations is nested in this framework for $\alpha = 1$. We calculate α from the ratio of the elicited beliefs about the returns to experience, ζ_s and β_s (see Table 2) and the estimated reduced-form parameters for the realized contribution of part- and full-time years of experience $\gamma_{s,F}$ and $\gamma_{s,P}$ (see Table 4),

$$\alpha_s = (\beta_s/\zeta_s)/(\gamma_{s,P}/\gamma_{s,F}) \tag{9}$$

It is important to note that in this specification, individuals do not update beliefs. This assumption can be justified in two ways. First, previous findings suggest that the part-time penalty is as good as absent in the short-run (Manning & Petrongolo 2008). It only emerges after longer part-time employment spells. Given the dynamics, it is plausible that both the existence as well as the magnitude of the penalty are hard to gauge in a real-life setting. The penalty can only be observed by an individual who chooses to work part-time for multiple years in a row and compares herself to a similar coworker who has spent the time working full-time on the same job. Second, the expectations data presented in Table 1 suggest that older individuals overestimate wage growth in part-time employment in the same way as young individuals with less labor market experience. This provides further evidence that learning does not seem to take place as individuals progress through their working careers.

5.5 Estimation and Identification

Estimation proceeds in two stages. In the first stage, we use the SOEP sample to estimate the exogenous processes of the model; the rate of marriage and divorce, the employment and earnings process of the male spouse, and births over the life-cycle. We further use the estimated reduced-form parameters of the returns to part-time and full-time experience and set the scale of the wage shock to a level such that it fits the variance of wages. The specifications for the different processes and estimation results are presented in Appendices Appendix IV.2 and Appendix IV.3.

In the second stage of the estimation, we use indirect inference to estimate the parameters in preferences. Intuitively, we specify an auxiliary model that summarizes important aspects of observed (i.e., actual) behavior and behavior in a sample that we simulate using the decision rules and other equations of motion given by the life-cycle model. Parameter values are then chosen to maximize the similarity between the observed and simulated behaviors, as viewed from the perspective of the auxiliary model. Formally, let ω denote the collection of parameters to be estimated in the second stage. The indirect inference estimator of ω is given by:

$$\widehat{\omega} = \underset{\omega}{\operatorname{argmin}} \left(\widehat{\psi} - \widehat{\psi}(\omega)\right)' \Sigma \left(\widehat{\psi} - \widehat{\psi}(\omega)\right), \tag{10}$$

where $\widehat{\psi}$ denotes the auxiliary parameter estimates based on observed behavior, including estimates that we obtain from our SOEP sample, $\widehat{\psi}(\omega)$ denotes the auxiliary model parameter estimates obtained using a sample simulated from the life-cycle model with parameter values ω, and Σ is a diagonal weighting matrix.[18]

Table 5: Moments

Name	#	Description
Education choice rates	234	Education specific choice prob. for each age.
Child present choice rate	468	Education specific choice prob. for each age, with/without children.
Age range share	36	Education specific employment share when kids are in certain age ranges.

6 Results

6.1 Parameter Estimates

First, we evaluate the effects of the differential returns to full-time and part-time experience obtained from the reduced-form analyses over the life-cycle, using the structural model. Figure 3 shows how for different levels of education, hourly wages in part-time employment evolve over time relative to hourly wages in full-time employment. When entering the labor market, hourly wages in full-time and part-time employment do not differ. However, we see a strong decline in the relative wage trajectory for women with medium and high education. For women with low education, wages in full-time employment and part-time employment evolve quite similarly. The estimated experience profiles are very similar to the findings in previous studies (Blundell et al. 2016), who show considerably lower part-time penalties for women with high school and secondary education, respectively.

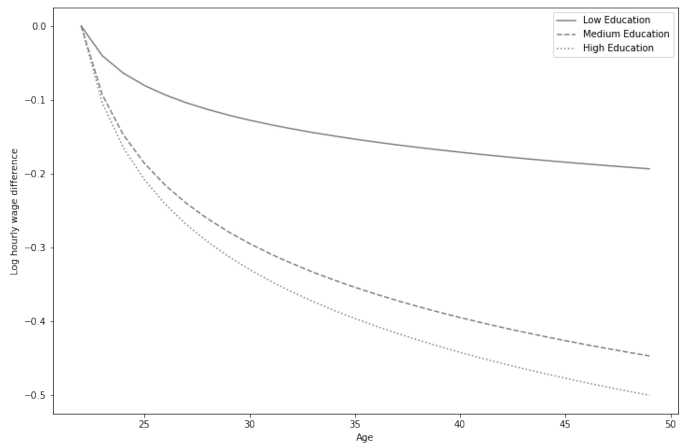


Figure 3: Part-Time Penalty

Relating the estimated part-time penalties to women's subjective expectations, we quantify the discrepancy between the expected and realized returns to experience. Specifically, we calculate the bias parameters α according to Equation 9 for each education group. The estimated bias is about two for women with low education. This suggests that these women expect a return to part-time experience relative to full-time experience which is twice as large as the relative realized return. The bias significantly increases for women with medium and

[18]When simulating samples from the life-cycle model, we plug in our estimates of the marriage and birth rates and the earnings process of the spouse. The weighting matrix has diagonal elements that are inversely proportional to the variances of the auxiliary model parameters. Variances for the auxiliary model parameter that we obtain from our samples are estimated using bootstrapping.

high education and is estimated to be about five. Why do we find this sizable education gradient in the bias? As we have documented above, irrespective of the educational level, women do not expect a part-time experience penalty. However, the realized part-time experience level is particularly pronounced for medium and college-educated women.

Table 6: Preference Parameters

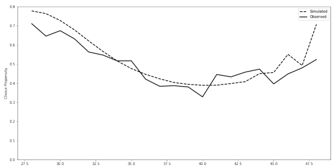
	Coeff. (1)	St. Error (2)	Coeff (3)	St. Error (4)
	Utility Parameters			
	All Employment		Part-time Employment	
Mother, High Education	0.30153	0.00026	-0.21747	0.00029
Mother, Medium Education	0.30921	0.00029	-0.26515	0.00029
Mother, Low Education	0.33356	0.00028	-0.23462	0.00030
No children, High Education	0.00360	0.00030	-0.01916	0.00098
No children, Medium Education	0.20256	0.00031	-0.00972	0.00075
No children, Low Education	0.34007	0.00023	-0.21579	0.00036
Child aged 0-2	0.22457	0.00036	-0.01594	0.00036
Child aged 3-5	0.13824	0.00025	-0.03687	0.00025
Child aged 6-10	0.09741	0.00022	-0.03660	0.00022
	Unobserved Heterogeneity in Cost of Work			
	Full-time Employment		Part-time Employment	
Unobserved type 1	-0.26720	0.00036	-0.18602	0.00042
Type 1:probability	0.50936 (0.00088)			

In Table 6, we turn to the structural parameters related to individual preferences. As mentioned above, we set the coefficient μ to -0.56, which translates to a risk aversion of 1.56 that is consistent with previous studies, see, e.g. Blundell et al. (2016). When interpreting the coefficients, it is important to note that positive and larger values of the preference parameters imply higher disutilities. Moreover, as defined in Equation 5, the coefficients of part-time work are additive to the coefficients of full-time work. For all groups, the coefficients of full-time employment have a positive effect and show that women experience disutility in full-time employment. As expected, disutility is stronger for women with children and specifically high when the age of the youngest child is between zero and two. The strong preference for part-time relative to full-time work is consistent with biased expectations about the returns of part-time experience. In our model, we capture that women over-estimate the returns to part-time experience. This suggests that women should place a higher value on part-time employment than in a standard model with rational expectations, and that the effect should be strongest for women with high education, who have the largest bias.

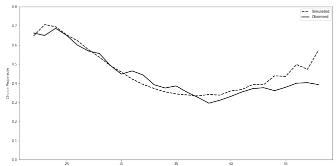
6.2 In-Sample Fit

The estimated life-cycle profiles of employment are very similar to the observed counterparts. In Figure 4, we show the age profiles of the three employment states for the different education groups. For all education groups, the model captures the decline in full-time employment during the ages when women have young children, as well as the increase at higher ages. The model further replicates the shares in part-time employment which are increasing with age, and the shares in non-employment which are markedly higher for women with low education.

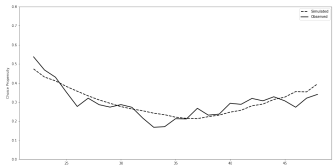
(a) **Full-Time, High Education**



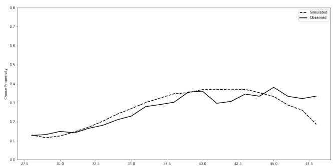
(b) **Full-Time, Medium Education**



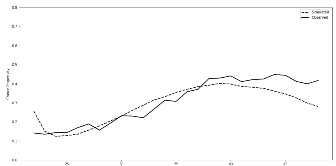
(c) **Full-Time, Low Education**



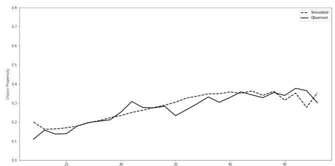
(d) **Part-Time, High Education**



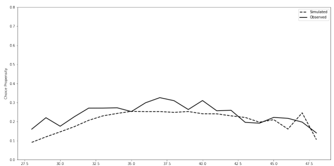
(e) **Part-Time, Medium Education**



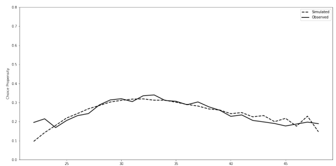
(f) **Part-Time, Low Education**



(g) **Unemployed, High Education**



(h) **Unemployed, Medium Education**



(i) **Unemployed, Low Education**

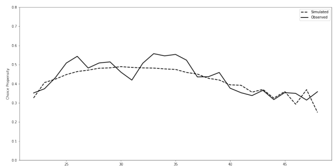


Figure 4: Life-Cycle Employment Profiles

7 Simulations

In the final section of the paper, we use the structural model to understand the implications of biased beliefs for employment and life-time earnings before taxes and transfers. Moreover, we quantify if policy reforms that incentivize full-time employment can change employment behavior and life-time earnings in the presence of biased beliefs.

7.1 Implications of Biased Beliefs

To understand the implications of biased beliefs about the returns to experience for employment and life-time earnings, we simulate a hypothetical scenario with de-biased expectations and compare this to the baseline scenario with biased beliefs. In the scenario with de-biased expectations, we set the bias parameter $\alpha = 1$ and assume that all individuals have rational expectations about the realized returns to experience. All other structural parameters are kept as in the baseline scenario.

Table 7: Life-Cycle Effects of Rational Beliefs

		Education		
	All	Low	Medium	High
Full-time employment	3.31	2.30	2.35	7.82
Part-time employment	-7.81	-4.78	-7.78	-12.99
Non-employment	4.50	2.48	5.43	5.17
Lifetime income	-0.45	0.58	-2.45	2.93

Notes: Employment effects are presented in percentage point change with respect to the baseline scenario. Lifetime income is presented as the relative change of the average lifetime income.

The overall effects for all women and by education over the life-cycle are summarized in Table 7. The effects strongly vary by education. Since women with low education have only a modest bias, we only find moderate changes in employment when women expect the true wage process. Over the full life-cycle, part-time employment among low educated women decreases by about five percentage points. Interestingly, both full-time employment and non-employment increase by about the same amount. This suggests that the lower expected returns to part-time experience in the de-biased scenario induces about half of the low-educated women to leave employment and the other half to increase working hours to full-time employment. The mixed employment effects explain why the effects on life-time earnings are close to zero among the low educated. For women with medium and high education, the effects are very different. For these groups, de-biasing has stronger employment effects. In the scenario in which the expected and realized returns to experience are consistent, the share of part-time employment is drastically lower (by 7.8 percentage points for women with medium education and by 13 percentage points for women with high education). The simulations further reveal that labor supply responses among the medium educated are dominated by substitution from part- to non-employment, whereas college-educated women are more likely to move from part-time employment into full-time employment. Correspondingly, we find the strongest life-cycle effects of de-biasing for college educated women, whose lifetime income would increase by about three percent, on average.

The results from this hypothetical scenario underline that the costs of biased beliefs can be substantial for the individual, but also for aggregate labor supply. Obviously this scenario is purely hypothetical and somewhat artificial, as it would require an information campaign teaching rational expectations about the returns to experience to all individuals. Moreover, the simulation analysis does not reflect any general equilibrium effects, which might occur when generating employment effects of this size.

Instead, policy makers can introduce reforms that incentivize women to choose full-time employment instead of part-time employment. Given biased beliefs about the returns to experience, it is not clear to what extent women will respond to these policies. We use the structural model to address this question in the next section.

7.2 Policy Reforms

We consider two prominent policy reforms that increase the incentives for full-time employment: i) the introduction of individual taxation instead of joint taxation with income splitting, and ii) the reduction of the costs for full-time child care. The fiscal effects of the two reforms are not comparable, therefore we abstract from a detailed welfare comparison and optimal policy analysis.

7.3 Individual Taxation

As described in Appendix Appendix V, according to the rules in Germany, couple households are taxed jointly with full income splitting. This system imposes a higher marginal tax rate on the secondary earner in the household, i.e. the partner with lower earnings, relative to individual taxation. Previous studies have documented that joint taxation induces strong disincentive effects for full-time employment. Moreover, as households with high taxable income and an unequal distribution of employment and earnings within the couple have a higher advantage from income splitting, joint taxation has important distributional implications, see e.g. Bick & Fuchs-Schündeln (2018) or Bach et al. (2020). Specifically, it favors households in which the spouse with higher earnings, in general the husband, works full-time and the other spouse, in general the wife, is non-employed or works part-time. Therefore, introducing individual taxation which taxes both spouses according to their individual taxable income provides incentives for women if they are the secondary earner in the household to increase working hours and to switch from non-employment to part-time or full-time employment.

Our simulations show that in line with the incentives, this policy reform would increase employment and earnings. As this reform has a direct effect on the current income, it has strong implications for part-time and full-time employment even in the presence of biased beliefs about the returns to experience (Table 8). We find that, on average, non-employment is reduced by about three percentage points over the working life. The size of the effect is similar across the different educational groups. At the same time, part-time and full-time employment increases. The effect for part-time employment (1.98 p.p.) is even larger than for full-time employment (1.05 p.p.). The larger effect for part-time employment has two sources. First, there is a direct incentive effect of individual taxation to change from non-employment to part-time employment. Second, given women's biased beliefs, the long-run costs of part-time employment are not incorporated, rendering this choice more attractive.

Table 8: Life-Cycle Effects of Individual Taxation

		Education		
	All	Low	Medium	High
Full-time employment	1.05	1.13	0.98	1.09
Part-time employment	1.98	2.30	1.99	1.44
Non-employment	-3.03	-3.43	-2.97	-2.53
Lifetime income	3.43	5.24	3.19	2.57

Notes: Employment effects are presented in percentage point change with respect to the baseline scenario. Lifetime income is presented as the relative change of the average lifetime income.

7.4 Child Care Costs

The availability of affordable child care is a central driver of female employment (Müller & Wrohlich 2020). Thus, to increase work incentives for women, policy makers could increase the provision of public child care, or subsidize child care costs. We simulate the effect of a child care reform and assume that child care costs for full-time working women is reduced to the level of child care cost for part-time workers.[19]

The reduction of child care costs also has notable employment effects. Overall, and for all education groups, the share of non-employment is reduced. We find that non-employment is on average 0.44 percentage points lower than in the baseline. Moreover, part-time employment is slightly lower. Both effects lead to an increase in full-time employment by over 0.6 percentage points, which results in an increase in life-time earnings by about 1.2 percent. The pattern by education groups is mixed. For all groups, we find a clear reduction in non-employment and part-time employment. The increase in full-time employment increases with the educational level, with college-educated women responding most. The effects on part-time employment are very low, in particular for low and medium educated women. This finding can be related to dynamic labor market processes. The costs for part-time child care and thus part-time employment does not change. Therefore, without dynamic effects, part-time employment should not change. However, the higher incentives for full-time employment for women with young children leads to higher human capital accumulation, which in turn has long-run effects for part-time employment even when children are older and child care costs are not relevant any more. The biased beliefs about the returns to part-time employment distort employment behavior, as the expected returns to part-time employment relative to full-time employment are too high.

Table 9: Life-Cycle Effects of Reduced Child Care Costs

		Education		
	All	Low	Medium	High
Full-time employment	0.60	0.32	0.70	0.80
Part-time employment	-0.17	-0.16	-0.08	-0.42
Non-employment	-0.44	-0.16	-0.62	-0.38
Lifetime income	1.17	0.63	1.40	1.10

Notes: Employment effects are presented in percentage point change with respect to the baseline scenario. Lifetime income is presented as the relative change of the average lifetime income.

8 Conclusion

In this paper, we analyze how biased beliefs about future prices affect individual decisions in a dynamic setting. Specifically, we analyze and quantify the effect of biased expectations regarding wage growth in part-time employment on life-cycle employment and earnings for women in Germany. We document that expectations about wage growth in part-time employment are severely upward biased. In particular, the survey responses imply that individuals do not expect any form of part-time penalty. In contrast, reduced form estimations show that wage growth rates in part-time work are close to zero and thus far lower than the elicited subjective expectations. In the second part of this paper, we develop a structural life cycle model of female employment to show how subjective expectations determine labor supply choices and dynamically translate into labor market outcomes. In the case at hand, misperceived gains from part-time work increase the propensity of part-time employment and lead to flatter long-run wage profiles.

[19] In this scenario, the costs for full-time child care are reduced by 162 Euros for under three-year-olds and by six Euros for three to six years olds per month.

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Appendix

Appendix I Data

This section provides additional details on the sample restrictions and the definitions of key variables in the analyses. We also show summary statistics of the two surveys.

Appendix I.1 Variable Description

We define *employment* based on annual measures of self-reported employment status[20], which is either full-time, part-time or non-working. In the structural model, working hours for each discrete employment category are modeled using the respective sample medians of agreed contractual working hours excluding overtime: 39 hours if full-time, 21 hours if part-time and 0 if non-working. *Work experience* in part-time and full-time is measured in years and is also constructed from self-reported employment status over time, except for first-time interviewed individuals who report detailed employment histories retrospectively, including years spent in full- and part-time employment. *Hourly wages* are constructed from monthly gross labor income and agreed contractual working hours excluding overtime. We trim wages at percentiles 1 and 99 from below and above for each survey year and convert wage rates to real terms using the consumer price index and base year 2018. For the structural analyses, we eliminate real wage growth by applying the detrending procedure proposed by Blundell et al. (2016). Figure SWA.1 shows the impact of trimming, inflation correction and detrending on the wage evolution. Likewise, *expected hourly wages* are also constructed based on agreed contractual working hours, trimmed and converted to 2018 real terms. *Education* is defined by the highest degree obtained, aggregated to three categories based on the CASMIN[21] educational classification: primary/basic vocational (low), Abitur/intermediate vocational (medium) and university (high). Completed years of education are modeled by the respective sample means: 10 years if low, 12 years if medium and 16 years if high education. We define *couple status* of a woman based on whether she shares the household with a partner (married or unmarried). We use detailed fertility histories as well as information about the number of children living in the household and the ages of these children to measure fertility and *motherhood*.

Appendix I.2 Additional Sample Restrictions in the Structural Analysis

This section presents additional sample restrictions that are required in the structural model to ensure consistency of employment spells over the life cycle.

We restrict the sample used in the structural analysis to individuals with consistent responses and changes in education and work experience. For women who have at least one spell of self-employment, we delete the subsequent employment paths. For women who give birth after age 42, we also delete the subsequent spells. We exclude individuals where employment state, experience or age of the youngest child is missing but include women with missing wage information if employment state is non-missing.

Appendix I.3 Comparison of SOEP and SOEP-IS

In this Appendix we provide evidence that the selected samples from the SOEP and the SOEP-IS are comparable and represent the same population. For most characteristics, samples show no significant differences. Samples are balanced in terms of average earnings, working hours, age, region, tenure, demographics, firm characteristics etc. There are significant but small differences in years of education and a larger proportion of married individuals in the SOEP-IS.

[20] We prefer to use the reported employment status as opposed to an hours-based measure of part-time vs. full-time employment for consistency reasons, first, because work experience in part-time and full-time in the SOEP is constructed based on self-reported employment status, second, because in eliciting wage expectations we use filters in the SOEP-IS questionnaire that are based on self-reported employment status.

[21] Comparative Analysis of Social Mobility in Industrial Nations

Figure SWA.1: Wage Evolution and Detrending

Notes: Plots show the effect of trimming, inflation correction and real detrending on the level and the evolution of gross hourly wages over the survey period for men and women in Western Germany (left panel) and Eastern Germany (right panel). Source: SOEP V. 35 (2018), Own calculations.

Table SWA.1: Comparison of the SOEP-Core and the SOEP-IS Samples

	SOEP-Core	SOEP-IS	Mean Diff. (Δ)	p-value (Δ)
Real gross hourly wage (in euros)	16.97	17.54	−0.56	0.20
Agreed working hours/week	34.42	33.45	0.97	0.13
Contractual working hours/week	31.86	30.55	1.31	0.02
Age (in years)	42.72	42.63	0.09	0.89
Eastern Germany (yes/no)	0.20	0.17	0.03	0.07
Married (yes/no)	0.68	0.78	−0.11	0.00
German born (yes/no)	0.79	0.80	−0.01	0.63
Education (in years)	12.13	12.72	−0.59	0.00
Tenure (in years)	9.86	9.49	0.38	0.48
Public sector (yes/no)	0.27	0.27	−0.00	0.88
Firm size > 200 (yes/no)	0.52	0.56	−0.03	0.25
Observations	24,929	473		

Notes: GSOEP 2016-2018. Women only. All estimates weighted.

Appendix II Earnings Expectations

Appendix II.1 Survey Questions (Example Screenshot)

Below, we present a screenshot of selected questions in the 2018 questionnaire (in German).

Ask only if **Q516 - PERW**,1 or **Q516 - PERW**,2

Q554 - IVT01: Einleitung Vollzeit/Teilzeit — **Text**

Not back

Die folgenden Fragen beziehen sich abermals auf Ihre Einkommenssituation.

Ask only if **Q516 - PERW**,1

B114 - B157: Vollzeit — **Begin block**

B115 - B159: Beibehalten der Arbeitsstunden — **Begin block**

Q555 - XX1A0_neu: Einleitung Beibehaltung der Arbeitsstunden — **Text**

Nehmen Sie an, Sie arbeiten auch in den kommenden Jahren weiter in Vollzeit, unabhängig davon, ob Sie in Wirklichkeit eine Arbeitsreduktion oder ähnliches planen. Denken Sie bitte an Vollzeitjobs, die Sie mit Ihrer Qualifikation ausüben können.
Sollten Sie in Wirklichkeit für die Zukunft eine Arbeitsreduktion oder ähnliches planen, nehmen Sie bitte dennoch an, in den kommenden Jahren weiter Vollzeit zu arbeiten.

Scripter notes: PERW,1

Q556 - XX1A1: Erwartetes Brutto ein einem Jahr — **Numeric**

Max = 999999

Was denken Sie ist Ihr monatliches Bruttogehalt in einem Jahr?

______Euro

997 Keine Angabe **Position fixed* **Exclusive*

Scripter notes: Bitte als "______ Euro" programmieren.

Ask only if **Q556 - XX1A1** >= 0

Q557 - XX1A1a: Wahrscheinlichkeit weniger Gehalt 1 Jahr — **Numeric**

Not back | Max = 100

Wie wahrscheinlich denken Sie ist es, dass Ihr Vollzeitjob ein Bruttogehalt in einem Jahr von weniger als [XX1A1-20%] pro Monat einbringt?

______Prozent

Bitte geben Sie Ihre Antwort in Prozent an. 0% bedeutet, dass Sie es für ausgeschlossen halten, 100% bedeuten, dass Sie sich sicher sind. Mit den Prozentangaben dazwischen können Sie Ihre Einschätzung abstufen.

Figure SWA.2: SOEP-IS Questionnaire 2018: Example

Appendix II.2 Survey Questions (Translation)

We provide an English translation of the survey questions on earnings expectations below.

Future earnings in current state: full-time (part-time) working woman

Suppose you continue to work full-time (part-time) in the coming years, regardless of whether you are actually planning a work reduction or anything similar. Please think about full-time jobs (part-time jobs) that you can perform with your qualification. If, in reality, you are planning to reduce (increase) your workload, please still assume for the moment that you continue to work full-time (part-time) in the next years.

Point estimate:

What do you think is your gross monthly income ...

1. ... in 1 year?
2. ... in 2 years?
3. ... in 10 years?

Uncertainty:

How likely do you think it is that ...

1. ... in 1 year, ...
2. ... in 2 years, ...
3. ... in 10 years, ...

your full-time job (part-time job) yields a gross income of less than X-20 % per month?
Please report your answer in percent. 0% means that you consider it impossible, 100% means that you are certain. You can use the percent values in between to graduate your answer.
[Note: X is the individual-specific response to the corresponding point-estimate question.]

How likely do you think it is that ...

1. ... in 1 year, ...
2. ... in 2 years, ...
3. ... in 10 years, ...

your full-time job (part-time job) yields a gross income of more than X+20 % per month?
Please report your answer in percent again etc.

Contemporaneous earnings in counterfactual state: full-time (part-time) working woman

Please imagine you were to switch to a part-time job (full-time job) from now on, working 20 (40) hours per week. Please only consider part-time jobs (full-time jobs) that you could carry out with your current level of qualification.

Point estimate:

What gross monthly income ...

...do you expect to earn when working part-time at 20 hours (full-time at 40 hours) per week?

Uncertainty:

How likely do you think it is that ...

...a part-time (full-time) position at 20 hours (40 hours) yields a gross income of less than X-20% per month? Please report your answer in percent again etc..

How likely do you think it is that ...

...a part-time (full-time) position at 20 hours (40 hours) yields a gross income of more than X+20% per month?
Please report your answer in percent again etc.

Future earnings in counterfactual state: full-time (part-time) working woman

Now suppose that you continue to work part-time (full-time) in the coming years, working 20 (40) hours per week.

Point estimate:

What do you think is your gross monthly income ...

1. ... in 1 year?
2. ... in 2 years?
3. ... in 10 years?

Uncertainty:

How likely do you think it is that ...

1. ... in 1 year, ...
2. ... in 2 years, ...

3. ... in 10 years, ...

your part-time job (full-time job) yields a gross income of less than X-20 % per month?

Please report your answer in percent again etc.

How likely do you think it is that ...

1. ... in 1 year, ...
2. ... in 2 years, ...
3. ... in 10 years, ...

your part-time job (full-time job) yields a gross income of more than X+20 % per month?

Please report your answer in percent again etc.

Appendix II.3 Robustness: Probabilistic Belief-Elicitation

In our main specification, we use reported point estimates of expected wages. In this section we present estimates of central tendency for expected wages based on the probabilistic questions from SOEP-IS wave 2018. We use reported probabilities for earning less than 80 percent and more than 120 percent of the respective point estimate and nonparametric spline interpolation to fit smooth individual-specific cumulative density functions (C.D.F.s) that pass through all reported probabilities. This approach imposes weaker assumptions than parametric fits (Bellemare et al. 2012). Specifically, we use piece-wise cubic hermite interpolating polynomials, a wage grid with a stepsize of 1 Euro, a lower bound of zero and an upper bound equal to the 99th percentile of doubled point estimates to construct individual-specific C.D.F.s.[22]

Table SWA.2: Sensitivity: Probabilistic Belief-Elicitation

	Full-time			Part-time		
	1 year	2 year	10 year	1 year	2 year	10 year
Central tendency						
Reported point estimate	20.7	22.0	23.3	22.0	22.2	26.0
Subjective mean	22.7	23.5	25.7	23.3	24.0	28.4
Subjective median	21.3	22.2	23.1	21.8	22.3	26.2
Uncertainty						
Std.Dev.	5.3	4.9	9.2	6.1	6.2	9.6
IQR (P75-P25)	6.2	5.2	9.7	6.9	7.4	10.1
N	96	84	71	92	92	75

Notes: SOEP Innovation Sample (2018). Cells contain sample averages of expected gross hourly wage in euros. Subjective mean, median and uncertainty calculated from probabilistic questions.

Sample means of reported point estimates and probabilistic measures of central tendency and uncertainty based on fitted C.D.F.'s are presented in Table SWA.2. Figures SWA.3 and SWA.4 show the corresponding distributions. Individuals assign most probability mass to values close to the point estimates, and similar mass to the tails. Measures of central tendency based on fitted C.D.F.'s (subjective mean, median) are therefore close to the reported point estimates, supporting our main specification.

[22] Interpolation is conducted based on MATLAB's PCHIP.

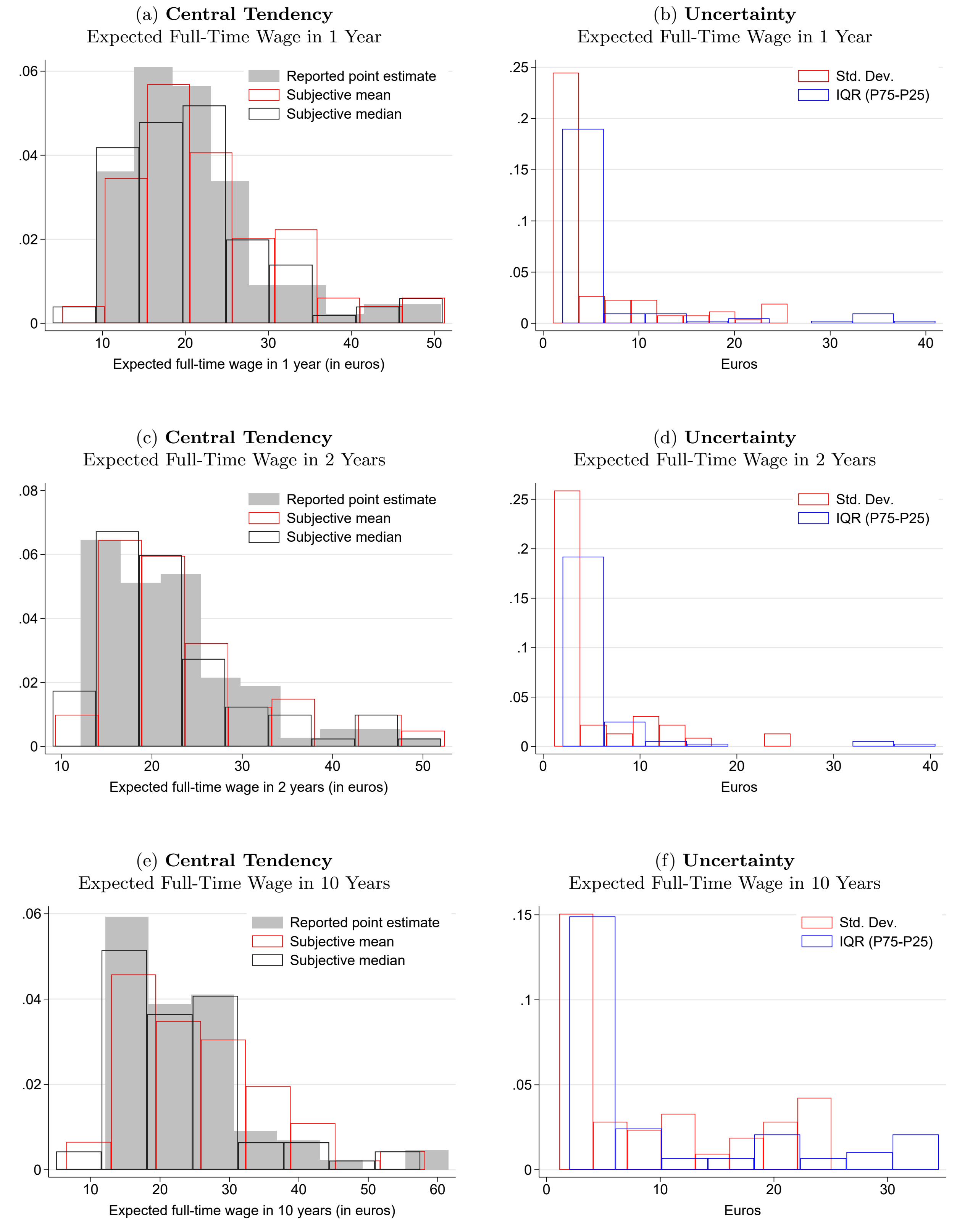


Figure SWA.3: Distribution of Central Tendency and Uncertainty in Full-Time Wage Expectations

Notes: Source: SOEP-IS (2018), Own calculations.

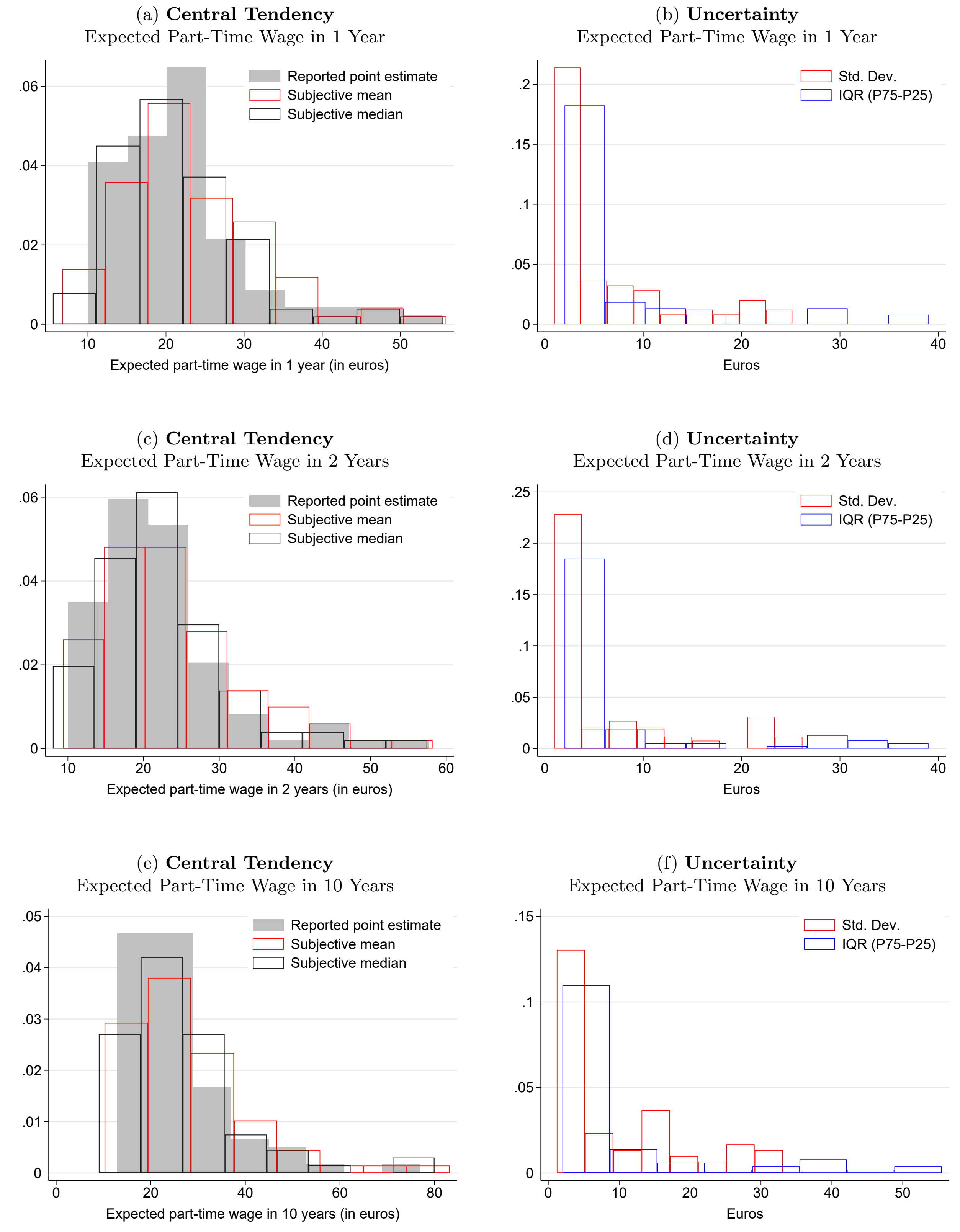


Figure SWA.4: Distribution of Central Tendency and Uncertainty in Part-Time Wage Expectations

Notes: Source: SOEP-IS (2018), Own calculations.

Appendix II.4 Robustness: Specification with Experience in Levels

Table SWA.3: Expected Annual Returns to Full-Time and Part-Time Experience: Experience in Years

	Total (1)	Low education (2)	Medium education (3)	High education (4)
Experience in full-time	0.014***	0.015***	0.014***	0.014***
	(0.001)	(0.002)	(0.001)	(0.003)
Experience in part-time	0.017***	0.015***	0.016***	0.019***
	(0.001)	(0.002)	(0.002)	(0.002)
Difference part-/full-time	0.002*	0.000	0.002	0.004*
	(0.001)	(0.002)	(0.002)	(0.002)
N	1,926	182	1,281	463

Notes: SOEP Innovation Sample (2016-2018). Unbalanced panel. Dep. Var. = Expected log gross hourly wage. Fixed Effects regressions excluding t=0. Standard errors clustered at the person-level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix II.5 Additional Results: Heterogeneity in Earnings Expectations

Table SWA.4: Heterogeneity in Expected Returns to Experience

	Log full-time experience		Log part-time experience		Mean Difference (β)		N
	β	s.e.	β	s.e.	β	s.e.	
All women	0.079***	(0.006)	0.092***	(0.008)	0.013*	(0.007)	1,926
Employment status							
Full-time workers	0.088***	(0.009)	0.082***	(0.016)	−0.007	(0.015)	867
Part-time workers	0.071***	(0.008)	0.101***	(0.009)	0.030***	(0.010)	1,059
Education							
Low	0.082***	(0.013)	0.083***	(0.011)	0.001	(0.013)	182
Medium	0.078***	(0.007)	0.089***	(0.010)	0.011	(0.010)	1,281
High	0.080***	(0.015)	0.104***	(0.013)	0.024*	(0.012)	463
Income							
Low (< P25)	0.055***	(0.009)	0.063***	(0.005)	0.008	(0.008)	423
Medium (P25-P75)	0.075***	(0.005)	0.082***	(0.006)	0.006	(0.006)	979
High (> P75)	0.082***	(0.008)	0.101***	(0.015)	0.018	(0.013)	524
Age							
< 35 years	0.104***	(0.011)	0.123***	(0.019)	0.018	(0.019)	506
35-45 years	0.078***	(0.007)	0.089***	(0.015)	0.011	(0.015)	503
> 45 years	0.064***	(0.010)	0.076***	(0.008)	0.012**	(0.006)	917
Region							
Eastern Germany	0.059***	(0.022)	0.076***	(0.017)	0.017*	(0.009)	372
Western Germany	0.084***	(0.006)	0.096***	(0.008)	0.012	(0.009)	1,554

Notes: GSOEP Innovation Sample (2016-2018). Unbalanced panel. Dep.Var. = log expected gross hourly wage. Estimates from fixed effects regressions, excluding t=0. Standard errors clustered at the person-level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix II.6 Robustness: Specification with Real Wages

Table SWA.5: Sensitivity: Inflation-Adjustment

	Total (1)	Low education (2)	Medium education (3)	High education (4)
Log experience in full-time	0.027***	0.030**	0.027***	0.028*
	(0.006)	(0.013)	(0.007)	(0.015)
Log experience in part-time	0.040***	0.031**	0.037***	0.052***
	(0.008)	(0.011)	(0.010)	(0.013)
Difference part-/full-time	0.013*	0.000	0.011	0.024*
	(0.007)	(0.013)	(0.010)	(0.012)
N	1,926	182	1,281	463

Notes: SOEP Innovation Sample (2016-2018). Unbalanced panel. Dep. Var. = Deflated expected log gross hourly wage, assuming 1 percent annual inflation. Fixed Effects regressions excluding t=0. Standard errors clustered at the person-level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix II.7 Robustness: Belief-Elicitation based on Hourly Wage Information

Table SWA.6: Sensitivity: Belief Elicitation in Terms of Hourly Wages

	Total (1)	Low education (2)	Medium education (3)	High education (4)
Log experience in full-time	0.111***	0.110***	0.108***	0.119***
	(0.009)	(0.025)	(0.011)	(0.022)
Log experience in part-time	0.099***	0.112***	0.099***	0.093***
	(0.007)	(0.023)	(0.009)	(0.009)
Difference part-/full-time	−0.012	0.002	−0.008	−0.026
	(0.008)	(0.017)	(0.008)	(0.022)
N	537	37	366	134

Notes: SOEP Innovation Sample (2019). Unbalanced panel. Dep. Var. = Expected log gross hourly wage. Expectations elicited in terms of hourly wages instead of monthly earnings. Fixed Effects regressions excluding t=0. Standard errors clustered at the person-level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix III Control Functions

In this Appendix we provide information about the first stage regressions for the control functions which we estimate separately for the three education groups. For identification we exploit variation in the tax and transfer system between the years 1992 and 2018 and simulate for all women the net household income out-of work, in part-time employment and in full-time employment. We then use different functional forms of the residualized simulated incomes[23] in the three employment states in addition to the number of children as instruments to construct the control functions.

In more detail we introduce control functions to account for selection into employment (λ^e), selection into full-time work (λ^h), and endogeneity of experience in part-time employment (λ^f) and full-time employment (λ^p).

Appendix III.1 Selection into Employment

We estimate the selection into employment by probit, using the number of children and simulated income in non-employment as instruments.

Table SWA.7: First Stage - Employment

	Low Education	Medium Education	High Education
Simulated income (non-employment)	0.244***	0.196***	0.246***
	(0.027)	(0.022)	(0.031)
One child	-0.255***	-0.514***	-0.543***
	(0.027)	(0.023)	(0.036)
Two children	-0.708***	-0.794***	-0.781***
	(0.032)	(0.026)	(0.039)
Three or more children	-1.320***	-1.300***	-1.153***
	(0.041)	(0.036)	(0.059)
Eastern Germany	-0.331***	0.013	0.471***
	(0.041)	(0.027)	(0.038)
Constant	0.372***	0.983***	0.963***
	(0.021)	(0.020)	(0.030)
N	52,231	75,419	29,288

Notes: SOEP v35, estimated by Probit. Sample includes women who work and who do not work. All models include a dummy for Eastern Germany. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The instruments are highly significant for all education groups. As expected children have a negative effect on employment. In contrast, the simulated income in non employment has a positive effect on employment which is related to the variation in out of work transfers. Women with high labor market attachment are more likely to receive unemployment benefits which are in general more generous than means-tested transfers. This explains the positive effect of simulated income in non-employment on selection into employment.

Appendix III.2 Selection into Full-Time Employment

The selection process into full-time employment is explained by the number of children in different age groups and the woman's own age. In addition we construct instruments based on the residualized simulated income in part-time and in full-time employment[24]: the simulated income in full time work and the difference in

[23] We follow Costa Dias et al. (2020) and regress the simulated income on number of children eligible for transfers, household size and marital status to capture potential changes in demographic variables over time. Thus the variation in the residuals over time can be attributed to changes in the tax and transfer system. We then use the residualized income as instruments.

[24] The disposable household incomes are simulated for a part-times scenario (20 hours/week) and a full-time scenario (40 hours/week).

simulated incomes in full-time and part-time employment. The instruments are in general highly predictive. Most importantly, the difference in the simulated income between full-time and part-time employment has a positive and significant effect on the selection into full time employment for all education groups. Similar to Costa Dias et al. (2020) we do not find a clear pattern for the simulated income in full time employment.

Appendix III.3 Experience in Full-Time and Part-Time Employment

The central instrument for the accumulated experience in full-time and in part-time employment is again the simulated income in full-time and the simulated income difference between full-time and part-time employment. As expected, for full-time experience the correlation with the simulated income difference is positive while for part-time experience this variable is negative. The additional instruments, i.e the simulated income in full-time employment and the variables related to age and children are in general highly significant and have the expected sign.

Table SWA.8: First Stage - Full-Time Employment

	Low Education	Medium Education	High Education
Difference FT- to PT-Residuals	1.043***	0.573***	0.742***
	(0.149)	(0.114)	(0.204)
Simulated income (FT-Residuals)	-0.070	-0.081**	0.146**
	(0.049)	(0.036)	(0.065)
Age	0.133	0.320***	0.551***
	(0.084)	(0.059)	(0.111)
Age^2	-0.004*	-0.008***	-0.014***
	(0.002)	(0.002)	(0.003)
Age^3	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Age oldest child: 1y	-1.241***	-1.808***	-1.266***
	(0.273)	(0.139)	(0.198)
Age oldest child: 2y	-1.417***	-1.700***	-1.443***
	(0.210)	(0.107)	(0.145)
Age oldest child: 3y	-1.411***	-1.619***	-1.304***
	(0.195)	(0.101)	(0.143)
Age oldest child: 4y	-1.536***	-1.583***	-1.327***
	(0.180)	(0.098)	(0.146)
Age youngest child: 1y	-0.111	0.116	-0.092
	(0.174)	(0.099)	(0.141)
Age youngest child: 2y	-0.213	-0.174**	-0.018
	(0.132)	(0.072)	(0.093)
Age youngest child: 3y	-0.244**	-0.096	-0.000
	(0.114)	(0.066)	(0.095)
Age youngest child: 4y	-0.172	-0.130*	0.057
	(0.108)	(0.067)	(0.102)
Eastern Germany	0.493***	0.530***	0.534***
	(0.066)	(0.036)	(0.055)
Constant	-0.291	-2.980***	-6.133***
	(1.086)	(0.748)	(1.486)
N	26,669	53,207	21,956

Notes: SOEP v35, estimated by Probit. Sample includes only employed women. All models include a dummy for Eastern Germany, as well as additional children's age categories for older age groups, but results are only displayed for ages 1-4. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table SWA.9: First Stage - Full-Time Experience

	Low Education	Medium Education	High Education
Difference FT- to PT-Residuals	8.269***	2.885***	3.183***
	(1.052)	(0.566)	(1.075)
Simulated income (FT-Residuals)	0.364	0.096	0.472
	(0.323)	(0.171)	(0.321)
Age	0.079	0.030	1.486***
	(0.471)	(0.282)	(0.523)
Age^2	0.028**	0.034***	-0.012
	(0.012)	(0.008)	(0.014)
Age^3	-0.000***	-0.000***	0.000
	(0.000)	(0.000)	(0.000)
Age oldest child: 1y	-0.668	-1.009***	-0.865
	(0.718)	(0.363)	(0.542)
Age oldest child: 2y	-1.001*	-1.539***	-1.105***
	(0.524)	(0.219)	(0.334)
Age oldest child: 3y	-1.038**	-1.814***	-1.448***
	(0.488)	(0.211)	(0.354)
Age oldest child: 4y	-2.058***	-2.605***	-2.105***
	(0.462)	(0.216)	(0.372)
Age youngest child: 1y	-0.354	-0.134	-0.038
	(0.566)	(0.311)	(0.435)
Age youngest child: 2y	-0.928**	-0.432**	-0.253
	(0.427)	(0.178)	(0.278)
Age youngest child: 3y	-1.421***	-0.759***	-0.231
	(0.358)	(0.170)	(0.292)
Age youngest child: 4y	-0.979***	-0.670***	-0.281
	(0.364)	(0.180)	(0.324)
Eastern Germany	5.998***	3.830***	5.722***
	(0.529)	(0.210)	(0.312)
Constant	-10.463*	-13.576***	-31.950***
	(5.720)	(3.296)	(6.584)
N	26,681	53,209	21,962

Notes: SOEP v35, estimated by OLS. Sample includes only employed women. All models include a dummy for Eastern Germany, as well as additional children's age categories for older age groups, but results are only displayed for ages 1-4. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table SWA.10: First Stage - Part-Time Experience

	Low Education	Medium Education	High Education
Difference FT- to PT-Residuals	-5.191***	-2.613***	-1.980**
	(0.801)	(0.468)	(0.835)
Simulated income (FT-Residuals)	0.629*	0.359**	-0.366
	(0.321)	(0.143)	(0.262)
Age	0.099	0.520**	-0.641
	(0.364)	(0.231)	(0.405)
Age^2	-0.006	-0.020***	0.014
	(0.010)	(0.006)	(0.010)
Age^3	0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
Age oldest child: 1y	0.333	0.946***	0.157
	(0.487)	(0.240)	(0.437)
Age oldest child: 2y	0.452	0.952***	0.177
	(0.330)	(0.156)	(0.246)
Age oldest child: 3y	0.425	1.159***	0.437
	(0.327)	(0.151)	(0.282)
Age oldest child: 4y	1.044***	1.642***	0.873***
	(0.312)	(0.157)	(0.308)
Age youngest child: 1y	0.097	-0.624***	-0.132
	(0.375)	(0.209)	(0.337)
Age youngest child: 2y	0.054	-0.210	0.005
	(0.264)	(0.137)	(0.207)
Age youngest child: 3y	0.386	-0.128	-0.000
	(0.249)	(0.133)	(0.219)
Age youngest child: 4y	-0.044	-0.243*	0.072
	(0.248)	(0.141)	(0.246)
Eastern Germany	-3.382***	-2.366***	-2.548***
	(0.378)	(0.172)	(0.230)
Constant	0.326	-2.980	10.830**
	(4.383)	(2.676)	(5.108)
N	26,681	53,209	21,962

Notes: SOEP v35, estimated by OLS. Sample includes only employed women. All models include a dummy for Eastern Germany, as well as additional children's age categories for older age groups, but results are only displayed for ages 1-4. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix III.4 Robustness: Wage Equation

In this Appendix, we present the results of a wage specification which additionally includes an indicator for part-time work in the current period, as well as a specification with linear and quadratic experience terms to allow for more flexibility of the functional form.

Table SWA.11: Estimated Returns to Full-Time and Part-Time Experience with Contemporaneous Part-Time Indicator

	Low Education		Medium Education		High Education	
	(1)	(2)	(3)	(4)	(5)	(6)
Log experience in full-time	0.105***	0.103***	0.179***	0.179***	0.225***	0.210***
	(0.012)	(0.013)	(0.007)	(0.008)	(0.013)	(0.014)
Log experience in part-time	0.035***	0.027**	0.029***	0.029***	0.041***	0.038***
	(0.009)	(0.012)	(0.005)	(0.008)	(0.009)	(0.014)
Part-time employed	0.033***	0.042***	0.032***	0.045***	0.043***	0.050***
	(0.009)	(0.010)	(0.006)	(0.006)	(0.010)	(0.009)
e		-0.045**		-0.041**		-0.089***
		(0.023)		(0.019)		(0.033)
h		-0.022		-0.038***		-0.024
		(0.023)		(0.013)		(0.023)
f		0.004		0.005*		0.019***
		(0.003)		(0.003)		(0.005)
p		0.005		0.004		0.018***
		(0.003)		(0.003)		(0.006)
Constant	2.214***	2.273***	2.236***	2.276***	2.366***	2.432***
	(0.030)	(0.034)	(0.018)	(0.021)	(0.033)	(0.036)
Prob > F ($lnE^{Full} = lnE^{Part}$)	0.0000	.0003	0.0000	0.0000	0.0000	0.0000
N	23,696	23,696	48,534	48,534	19,968	19,968

Notes: SOEP v35. All estimations include a fixed effect and an indicator for living in Eastern Germany. The control functions account for selection into employment (λ^e), selection into full-time employment (λ^h), and endogeneity of experience in full-time employment (λ^f) and in part-time employment (λ^p). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table SWA.12: Estimated Returns to Full-Time and Part-Time Experience: Linear-Quadratic Specification

	Low Education		Medium Education		High Education	
	(1)	(2)	(3)	(4)	(5)	(6)
Experience in full-time	0.017***	0.019***	0.031***	0.032***	0.041***	0.038***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Experience in part-time	0.009***	0.002	0.009***	0.009***	0.013***	0.010*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)
Squared experience in full-time/1,000	-0.211***	-0.187***	-0.497***	-0.509***	-0.635***	-0.591***
	(0.046)	(0.047)	(0.038)	(0.039)	(0.060)	(0.061)
Squared experience in part-time/1,000	-0.189***	-0.211***	-0.179**	-0.234***	-0.307*	-0.343**
	(0.071)	(0.071)	(0.071)	(0.072)	(0.158)	(0.161)
Part-time employed	0.035***	0.039***	0.032***	0.042***	0.038***	0.041***
	(0.009)	(0.010)	(0.006)	(0.006)	(0.009)	(0.009)
e		-0.059**		-0.030		-0.056
		(0.024)		(0.020)		(0.034)
h		0.006		-0.030**		-0.009
		(0.024)		(0.013)		(0.024)
f		0.002		0.004		0.019***
		(0.003)		(0.003)		(0.005)
p		0.013***		0.005		0.022**
		(0.005)		(0.004)		(0.009)
Constant	2.299***	2.356***	2.386***	2.420***	2.538***	2.579***
	(0.021)	(0.028)	(0.015)	(0.019)	(0.025)	(0.033)
Prob > F ($E^{Full} = E^{Part}$)	0.0184	0.0001	0.0000	0.0000	0.0000	0.0000
N	23,696	23,696	48,534	48,534	19,968	19,968

Notes: SOEP v35. All estimations include a fixed effect and an indicator for living in Eastern Germany. The control functions account for selection into employment (λ^e), selection into full-time employment (λ^h), and endogeneity of experience in full-time employment (λ^f) and in part-time employment (λ^p). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The central findings of these specification are very similar to the results of the main specification. Adding an indicator for part-time work in the current period does hardly affect the point estimates of the returns to part-time and full-time experience (Table SWA.11). Consistent with previous studies for Germany, see e.g. Paul (2016) or Schrenker & Zucco (2020) and other countries (Aaronson & French 2004, Hirsch 2005, Booth & Wood 2008) we find that conditional on the experience terms, there exists no large contemporaneous wage penalty of working part-time.[25]

In Table SWA.12, we present the results of the specification with linear and quadratic terms. The realized returns to full-time experience are larger than the returns to part-time experience. Returns to part-time experience are either not significant or very small in magnitude. An F-test on the equality of the returns to full- and part-time experience is rejected for all education groups.[26] Thus the central finding of a part-time experience penalty does not depend on the functional form of the wage equation.

Appendix IV Initial Conditions and Exogenous Processes

Appendix IV.1 Initial Conditions

Women enter the model at age 22 if they are low and medium educated and at age 24 if they are highly educated. To set the initial conditions of the exogenous variables, we use education-specific empirical shares to estimate the probability that at the age they enter, (i) a woman already has a partner, (ii) a woman already has a child, (iii) the age of the youngest child is 0/1/2/3 or 4 years, (iv) the amount of previously accumulated work experience in full-time and (v) in part-time employment is 0/1/2/3 or 4 years. Hence, we set the probability that a woman has more than 4 years of work experience by the age she enters the model to zero.

Appendix IV.2 Marriage, Divorce and Partner Earnings

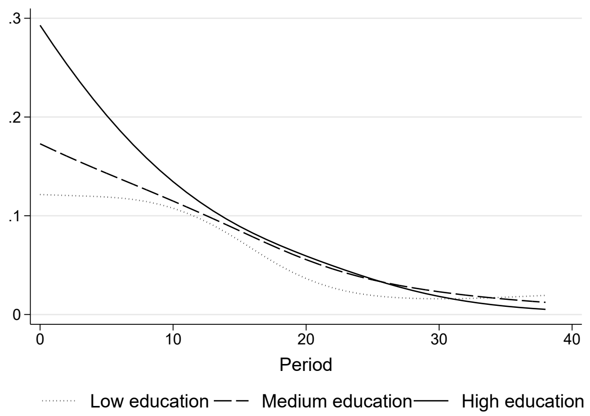
For women aged 22-60, we estimate the probability that a single woman finds a partner in a given year separately by education (low, medium or high) using logistic regressions with a cubic polynomial in female age. Analogously, we estimate the probability that a woman who had a partner in the previous period separates from her partner using logistic regressions with a cubic function in female age, again separately by education. Conditional on having a partner, we assume all men work full-time at 40 hours per week and predict the partner's log wage based on female education and female age up to a second order polynomial using OLS regressions.

Appendix IV.3 Fertility

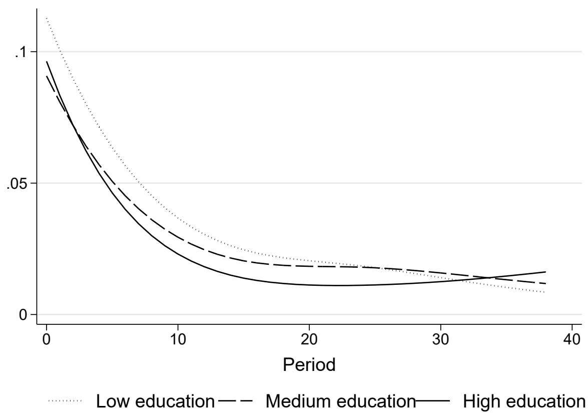
To estimate annual birth probabilities we estimate education-specific logistic regressions of child birth as a function of female age up to a third order polynomial for women in child-bearing age until age 42. We set birth probabilities to zero for women above age 42.

[25] Schrenker (2022) provides an overview about the international literature which finds mostly small to no effects of the current employment state on wages for female workers.

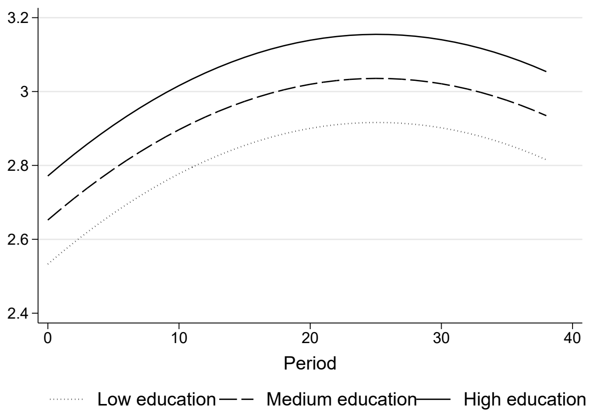
[26] Specifically, we test the joint equality of the linear and the quadratic experience coefficients.



(a) Partner Arrival



(b) Partner Separation



(c) Partner Log Wage

Figure SWA.5: Annual Probabilities for Partner Arrival and Separation and Predicted Partner Log Wage

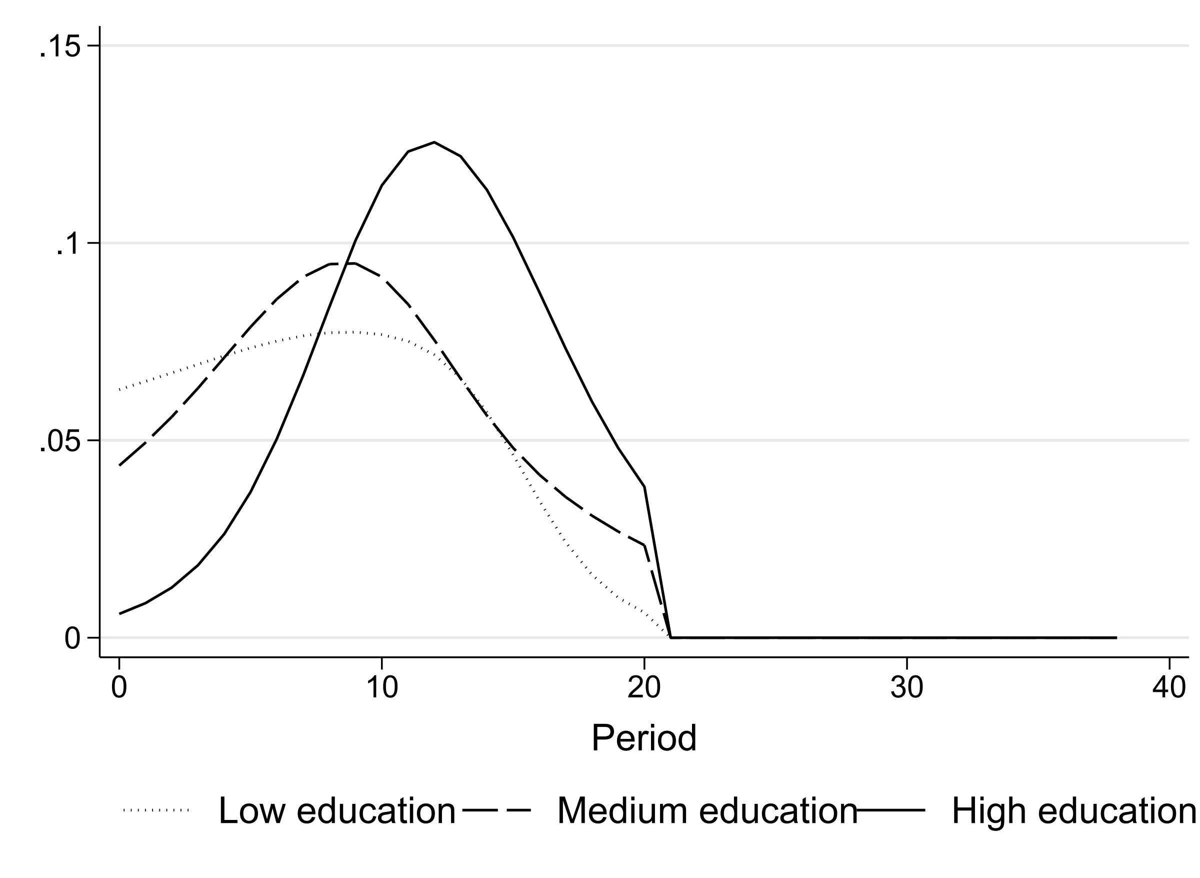


Figure SWA.6: Annual Birth Probabilities

Appendix V Tax and Transfer System

This Appendix describes the rules of the tax and transfer system, of child benefits and of child care costs and how these institutions affect the budget constraint (Equation 5.2). For the estimation of the structural model we focus on the period 2007-2018. During that time period the general structural of the tax and transfer system was only slightly changed.

Social Security Contribution and Income Taxation

Individuals pay social security contributions for health, unemployment and pension benefits. The social security tax, including contributions for health benefits, unemployment benefits, and pension benefits is a flat rate tax of 21,5% on individuals labor earnings below a cap of 63,000 euros per year.[27]

A progressive income tax is applied to household income, i.e., taxation is joint: a single household with taxable income of x and a married household with taxable income of $2x$ face the same average tax rate on taxable income.[28] Income tax is based on taxable household income, which in our model is equal to the taxable labor earnings all household members minus the household's tax-deductible social security contributions. Individual earnings in excess of 7,664 euros per year are taxable. Social security contributions can be deducted from taxable income. The solidarity surcharge (Solidaritaetszuschlag) is included in income tax and is equal to 5.5% of the household's tax liability, excluding social security contributions.

[27] Since, in the model individuals work either part- or full time they are always above this threshold of 'Minijobs' for which no social security payments apply.

[28] For a detailed description of the German income tax schedule, see Haan & Prowse (2017)

Unemployment Benefits and Means-Tested Transfers

Unemployment insurance provides partial income replacement to eligible non-employed individuals. In our model we follow Adda et al. (2017) and assume that all individuals who have been employed in the previous period are eligible to receive unemployment benefits for one year. The replacement rate is equal to 0.6 of net earnings [29] if no children reside in the individual's household or 0.67 if one or more children reside in the individual's household.

When unemployed are not entitled to unemployment insurance benefits they can receive social assistance. Social assistance is a universal household benefit that tops up the net income of households to a level that we call the 'social assistance income floor' ($\text{SAFloor}_{i,j,t}$). The social assistance that is available to a household is given by:

$$\widetilde{\text{SA}}_{i,j,t} \quad = \quad \max\{\text{SAFloor}_{i,j,t} - \widetilde{y}_{i,j,t}, 0\}, \tag{11}$$

where $\widetilde{y}_{i,j,t}$ is net household income before social assistance is included.

The social assistance income floor can be written as:

$$\text{SAFloor}_{i,j,t} \quad = \quad G \times E_{i,j,t}. \tag{12}$$

The social assistance income floor $\text{SAFloor}_{i,t}$ varies between household types. For singles, it is equal to 91 euros per week, a household receives in addition 82 euros for an adult partner and 59 euro for children . In addition households receive housing benefits which amount to 77.5 per week for a single and increase with the number of other household members by about 15 Euros per week.[30]

Social assistance benefits are means-tested based on net household income. In the model we approximate the means-testing rules: households are not eligible for social assistance benefits when one adult member of the household is employed.[31]

Child Benefits and Child Care Costs

A household receives child benefits for each dependent child (43 Euro per week). A household also receives parental leave benefits for newborns.

Specifically mothers receive parental leave benefits paid for a period of 12 or 14 months.[32]. The parents' benefit is not means-tested on household income and the amount of the benefit depends on earnings prior to birth. It replaces 67% of previous net earnings, but does not exceed 1800 euro per month and there is a floor of 300 Euro per months. We approximate the parents' benefit with 67 of potential net full time earnings.[33]

We assume that a household with one or more pre-school aged children must pay for full-time childcare if both spouses work full-time. A household incurs part-time childcare costs if the wife works part-time and the husband works full-time. A single woman with one or more pre-school aged children must pay childcare costs reflecting her hours of work. Following Geyer et al. (2015), we assume monthly childcare costs for a child younger than 3 years of 219 euros for part-time care and 381 euros for full-time care. The corresponding figures for a child aged between 3 and 6 years are 122 Euros and 128 euros.

[29] We deduct 30% (social security contributions and income taxation) from the gross earnings to calculate the relevant net earnings

[30] The numbers approximate averages over the different regions in Germany.

[31] This approximation has no major implication since in the model all males work full time, and women work at most part time hours.

[32] Mothers and fathers can either share their entitlement, in which case the leave is extended to 14 months, or, if only one parent takes the leave, it amounts to 12 months. We assume that only the mother is taking parental leave for 12 months

[33] We deduct 30% (social security contributions and income taxation) from the gross earnings to calculate the net earnings