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**Maximilian Blesch** (HU Berlin and DIW Berlin)

**Philipp Eisenhauer** (Amazon)

**Peter Haan** (FU Berlin and DIW Berlin)

**Boryana Ilieva** (HU Berlin and DIW Berlin)

**Annekatrin Schrenker** (FU Berlin and DIW Berlin)

**Georg Weizsäcker** (HU Berlin)

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Ludwig-Maximilians-Universität München | Humboldt-Universität zu Berlin
Spokesperson: Prof. Georg Weizsäcker, Ph.D., Humboldt University Berlin, 10117 Berlin, Germany
info@rationality-and-competition.de

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Maximilian Blesch†
Philipp Eisenhauer‡
Peter Haan§
Boryana Ilieva¶
Annekatrin Schrenker‖
Georg Weizsäcker**

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**Abstract**

Wage growth occurs almost exclusively in full-time work, whereas it is close to zero in part-time work. German women, when asked to predict their own potential wage outcomes, show severely biased expectations with strong over-optimism about the returns to part-time experience. We estimate a structural life-cycle model to quantify how beliefs influence labor supply, earnings and welfare over the life cycle. The bias increases part-time employment strongly, induces flatter long-run wage profiles, and substantially influences the employment effects of a widely discussed policy reform, the introduction of joint taxation. The most significant impact of the bias appears for college-educated women.

**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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†Humboldt-Universität zu Berlin, maximilian.blesch@hu-berlin.de

‡Amazon, peisenha@protonmail.com

§Freie Universität Berlin and DIW Berlin, phaan@diw.de

¶Humboldt-Universität zu Berlin and DIW Berlin, bilieva@diw.de

‖Freie Universität Berlin and DIW Berlin, aschrenker@diw.de

**Humboldt-Universität zu Berlin, weizsaecker@hu-berlin.de

# 1 Introduction

We investigate how possible misperceptions about long-run wage prospects contribute to the empirical patterns in women's labor supply. Despite sizable increases in most OECD countries' female labor force participation, gender imbalances in the labor market persist.[1] Selection effects can rationalize many short-run imbalances, but the dynamic effects of labor supply are harder to explain and raise additional issues (Goldin 2021). One crucial set of issues lies in the long-run consequences of entering part-time 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, Adda et al. 2017) Careers with considerable wage growth appear almost exclusively in full-time employment, whereas part-time wage profiles are essentially flat.

This leads to the question of 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 number of predictions: assessments of their possible earnings trajectories in both part-time and 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 and malleable, influencing economic outcomes (e.g., Coibion & Gorodnichenko 2012, Das et al. 2022, Roth & Wohlfahrt 2020, Fuster et al. 2022). Thus, we measure women's expectations about their earnings in both part-time and full-time employment scenarios, quantify the implications of these expectations for employment, lifetime earnings, and welfare, and evaluate a policy reform aimed at increasing labor supply.

In our sample, designed to represent employed women in Germany, we observe relatively 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 a ten percent increase in experience increases wages by about 0.7 to about 1 percent per year in full-time *and* in part-time employment. The estimates are very similar across educational groups. 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 with individual fixed effects and via a structural life-cycle model. For full-time experience, we estimate that a 10 percent increase in experience increases wages by 1 percent for the group with a low level of education and close to 2 percent for the individuals with medium and high levels of education. All of these estimates of realized returns confirm evidence from the UK by Blundell et al. (2016), while the finding of a strongly asymmetric expectation accuracy between full-time and part-time is novel in the literature, to our knowledge. (Notably, the analysis by Boneva et al. (2021), discussed below, finds a weaker asymmetry, albeit in a different context.)

Considering heterogeneity in beliefs, we document relatively small differences in belief biases between subgroups, most remarkably between full-time and part-time workers. Almost irrespective of current employment status, respondents fail to predict the difference in wage growth between full-time 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.

The structural model allows us also to assess the consequences of belief biases. The model incorporates relevant personal variables and aspects of a woman's decision problem in real life – not least its nature of dynamic

[1] In 2022, female employment rates averaged 62 percent across OECD countries. In Germany, the country under study here, the female employment rate reached 73 percent in 2022, compared to 59 percent in 2005 (OECD 2022). Germany is a typical example of OECD-wide trends. It is noteworthy that its part-time rate is high and increasing, see Section 4, and that cultural norms and "child penalties" in the wage level are viewed as influential factors for labor supply (Kleven et al. 2019).

optimization. Simulations of the model show that the bias translates into an increased propensity of part-time employment by more than 6 percentage points, on average, across the population of Germany's female women. This result is produced by counterfactually imposing rational expectations in the model and comparing its predictions to those generated from the full model with biased beliefs. About half of women would react to a hypothetical de-biasing by moving from part-time to non-employment, the other half would be switching from part-time to full-time work. Thus, the hypothetical de-biasing would not lead to an increase in employment. We find again the strongest employment effects for women with a college education: About 25 percent of them are currently in part-time employment, and more than 12 percentage points of them would change this status if they were de-biased. Corresponding to these estimates, we find that the bias has strong welfare effects. Following Low et al. (2010), we estimate the amount of per-year wage loss that is equivalent to the effect of the bias. The result is equivalent to 0.62 percent of lifetime consumption and, once again, the lion's share is driven by the group of college-educated women.

Finally, we study the implications of a tax reform on employment and life-time earnings that is widely discussed in Germany and recommended by the OECD, see e.g. OECD (2023): abandoning joint assessment of married couples' taxes. The reform would increase most married women's work incentives and we find that the bias boosts the effect of the reform, mainly because it depresses the female labor supply to start with. Many high-educated women work part-time in the wrong belief of not facing a wage penalty for it, which would be counteracted by the reform. The overall impact of the reform, in terms of increased working hours, is an increase of 0.31 percentage points in full-time employment and an increase of 2.75 percentage points in part-time employment, according to our estimates. Without bias, the effect on full-time employment would be markedly larger (3.85 percentage points) but the effect on part-time employment would be negative (-3.53 percentage points).

To derive these results, we design counterfactual questions and include them in the Innovation Sample of the German Socio-Economic Panel Study (SOEP-IS), a survey of private households that takes extensive measures for the 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. We can thus measure, at the individual respondent level, the perceived difference in returns to experience between full-time and part-time work.

We use two econometric strategies for the quantification of the effects. 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 variations 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 analog to the perceived returns: it features an equivalent data environment to the SOEP-IS. It includes cases of trajectories in part-time and full-time employment, 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 dynamic life-cycle model to estimate long-term wage trajectories together with dynamic employment choices. The model is a smaller version of Blundell et al. (2016) and Adda et al. (2017) with modifications specific to our purpose. 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 circumstances 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

[2] Schrenker (2020*a*) studies the perceived effect of part-time work on current wages, whereas we analyze expectations about future wage growth.

misperceptions affect the 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 us to leverage the model and quantify the effects of biased expectations and simulate policy reforms, as described above.

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, Gohl et al. 2022) and human capital formation and labor markets (Arcidiacono et al. 2017, Boneva et al. 2021, Delavande & Zafar 2019, Jäger et al. 2022, Wiswall & Zafar 2016)). We add to it our emphasis on biased long-run wage expectations, which we examine as a possible driver for human capital accumulation. Previous studies analyzed the effects of part-time work perceptions on current wages (Schrenker 2020*a*, Stevens et al. 2004) but not their effects on long-run outcomes.[3]

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), which allow for time-inconsistent preferences in the form of hyperbolic-discounting and Schneider (2020), which incorporates biased beliefs about labor market frictions.[4] We add to these approaches our quantification of the effect of misperceptions about the return to experience, 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 quantify the evolution of dynamic part-time wage penalties over the life span.[5]

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 is explained by social norms (Boneva et al. 2021), preferences (Adda et al. 2017), financial incentives (Bick & Fuchs-Schündeln 2017*a*), and fertility timing (Wasserman 2022). 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*a*, 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 and that it may, in some cases, be a mistake. Yet, misperceptions are rarely studied as drivers of women's career choices. Exceptions are two papers by Kuziemko et al. (2018) and Boneva et al. (2021). The former paper shows evidence that women underestimate the employment effects of motherhood, and the latter paper gives evidence that respondents *do* anticipate that part-time work has an effect on a hypothetical earnings history of a mother. The focus on motherhood sets the two papers apart from ours. Moreover, neither paper uses beliefs about the counterfactual of one's own potential outcomes – instead, they ask about other people's work lives. In contrast, we focus on misperceptions of *long-run* outcomes, which we find especially suitable for the study of misperceptions. 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 – equally so for men, by the way – and that this misperception corresponds to a sizable portion of part-time labor supply.

[3]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 appear 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. (2021a).

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

[5]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. 2018).

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 our 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.[6] 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 I.1. Appendix I.2 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. The 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. 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. We leverage the panel dimension in our control function regressions (Section 4) and in our structural analysis (Section 5). In addition, 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 are essential ingredients in 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 2016-2018 period. 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 when constructing the central moments for the structural model.[7] To study wage growth after completing education and before retirement We restrict the age range to women between 22 and 60. Our estimation samples contain all women after completing 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 the structural

[6]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).

[7]This restriction allows us to approximate the tax and transfer system with a single tax function as the most relevant rules did not change throughout the sample period.

model), we include non-employed women to account for the potential effects of selection into employment.[8] Women in marginal employment ('Mini-Jobs') are, however, always excluded.[9]

Our restricted SOEP core sample for the 1992-2018 period contains N=92,198 women-year observations, with approximately 3,400 women per period. The 2007-2018 sample for the structural analysis contains 67,526 women-year observations with about 5,600 women per period.[10] 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.

## 3.1 Survey instruments

The 21 survey questions that we include into 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 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. In contrast, part-time workers are asked to consider switching to a full-time position at 40 hours. Both groups are asked to report their expected current earnings in the hypothetical scenario, conditional on their qualification. Third and finally, respondents are asked to imagine remaining in the hypothetical scenario for one year, two years, and ten years and report their 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 deviations from the point estimate by more than 20 percent to be, separately in each direction. Appendix II contains a description of the exact wording of the survey questions and provides evidence that results based on probabilistic-answer formats are comparable (Table SWA.2).

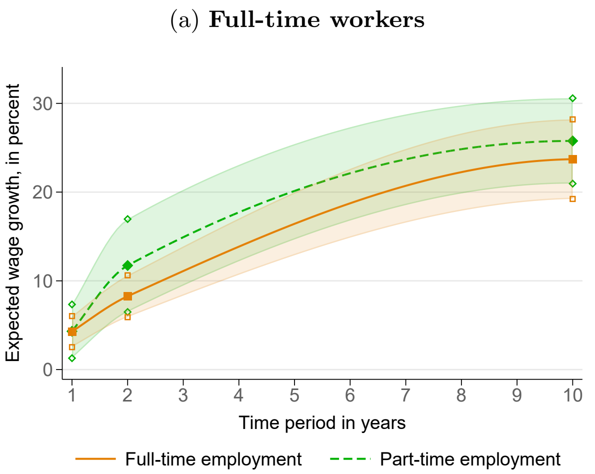
## 3.2 Perceived wage growth in full-time and part-time employment

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

[8]The difference in sample composition between the SOEP-IS and the SOEP core sample does not impede the comparison of expected and realized returns to experience. Results in Table 4 show that fixed effects account for selection effects. We include fixed effects in the SOEP-IS and SOEP core regression specifications and individual-specific disutility types in the structural framework, thus ensuring comparability.

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

[10]To construct the return to experience moments in the structural estimation, we use the full 1992-2008 sample.



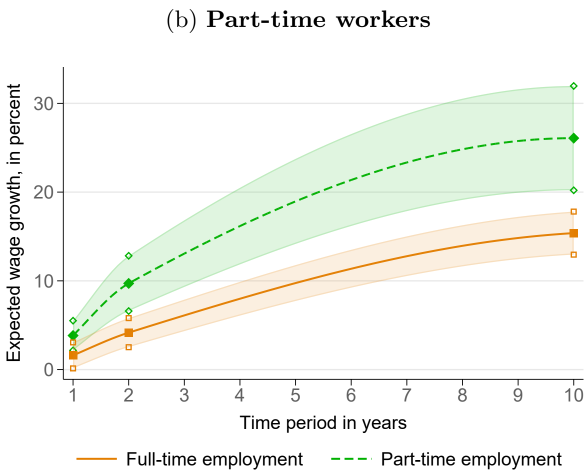




Figure 1: Expected wage growth in full-time and in part-time employment

*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 percent confidence bands. Markers are connected by a fitted smooth piece-wise interpolating polynomial. Observations used are from a balanced panel of women who gave valid responses for all 8 questions asking for point estimates (SOEP-IS 2016-2018).

Expected wage increases denote changes in percent relative to the respondent's wage in the year of the survey response. The depicted 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 Figure 1, we see that full-time working women expect wage growth to be almost exactly identical in full- and part-time employment. Part-time workers even expect stronger part-time wage growth compared to full-time wage growth. This pattern of a stronger increase in part-time wages is consistent with self-justification of part-timers in the survey response or other possible selections based on comparative advantages or preference-driven productivity differences (Bertrand & Mullainathan 2001). For any single respondent, the expectation that no part-time experience penalty exists may be accurate (recall that the questions ask about one's personal trajectories). Yet, in the aggregate, they are inconsistent with the previous literature and the estimates we provide in Section 4 and in our structural analysis.

Comparing expectations across time horizons, we see in Table 1 that women on average expect similar earnings growth in part-time and 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. Overall, the expected increase is concave in time. Reported 1-year-out expectations show, on average, perceived earnings increases of 4 percent in full-time employment and 3 percent in part-time employment (Table 1, first versus second column); after two years, respondents expect wages to increase by 6 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. The pattern of concavity in time is consistent with empirical observations (see, e.g., Breunig et al. 2021a).

Of the different subgroups that we consider in Table 1, none expects a part-time penalty in wage growth. However, relevant differences appear by the level of education, age, and region. Highly-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 in the high-education category 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, while women older than 45 years expect only an increase of 15 percent and 18 percent. These group-specific patterns, too, are in line with empirical findings about the realized returns to experience (Blundell et al. 2016, Breunig et al. 2021a). 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 – making it more remarkable that not a single subgroup of the population predicts a part-time wage penalty.

Table 1: Expected wage growth in part-time and full-time employment (in percent)

| | 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 now turn to regressions to describe the respondent's expectations and to prepare for comparison with realized wages. Analogous to standard wage regressions, we estimate the returns to experience in part-time and full-time employment *as expected by the survey respondents*:

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

Here, $Ew_{it}$ denotes the expected gross hourly wage that individual $i$ expects to earn at time $t$, with $t \in \{0, 1, 2, 10\}$.[11] The two experience variables, $E_{it}^{Part}$ for years in part-time employment and $E_{it}^{Full}$ for years in full-time employment, are specified according to the horizon of the questions about expectations, taking the values zero for observations where the left-hand-side variable is today's log wage or, depending on the scenario that the question asks about, one year, two years and ten years.[12] Our main specification also includes an individual-specific fixed effect $\mu_i$. In contrast, an alternative specification omits the fixed effects but includes a

[11]We focus on hourly wages here, for 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 scenarios specified in the survey instruments: 20 hours for part-time and 40 hours for full-time employment, respectively.

[12]Because of the log transformation of experience, we add one year of experience to $E_{it}^{Full}$ and $E_{it}^{Part}$, allowing us to also include women with zero experience in either full-time or part-time.

vector of individual-specific covariates that are constant over $t$ and vary by respondent $i$.

The log specification of the experience terms is used to capture potential non-linear effects of experience. In a set of sensitivity checks, we find that the main results are robust to variations of functional forms or sample splits (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 columns 1 and 2 only use the information on expected future wages. In contrast, the estimations in columns 3 and 4 also include information about observed and counterfactual wages in the current period (t=0).[13]

Table 2: Log expected return 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, migration background, firm size, public sector employment, marital status and number of children. The sample size between FE and POLS differs because of missing information in control variables.

In line with the descriptive evidence, the regression results indicate that subjective expectations about returns to experience are similar for part-time employment and full-time employment. Depending on the specification and 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 of full-time experience amounts to 0.08, i.e. an increase in full-time experience by 10 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 subjectively expected returns to experience between part-time work and full-time work is small; in those specifications where the corresponding coefficients differ significantly, the effect is higher for the returns to part-time work than for full-time work.[14]

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). We do not find a statistically significant difference in the expected returns to part-time and full-time experience for any of the education groups; i.e., no subgroup expects a penalty for the experience in part-time. In Table SWA.5, we extend the heterogeneity analysis and repeatedly confirm the same pattern for different subgroups.

[13] In estimating the perceived returns, we include in our sample all women with valid responses to at least one expectation question (unbalanced panel). In Figure 1 and Table 1, we used a (smaller) sample of women with valid responses to all eight expectation questions (balanced panel) because Figure 1 and Table 1 show perceived changes in growth rates which require multiple data points at the individual level. We show in the Appendix that estimates of the perceived returns based on the balanced panel are very similar to those from the unbalanced panel (Table SWA.4).

[14] We note again that the result is in apparent contrast to Boneva et al. (2021) whose survey respondents predict that part-time working mothers have earnings losses. As Boneva et al. (2021) ask about scenarios that describe the lives of others, a potential explanation for both sets of findings is that survey respondents are generally aware of part-time career penalties (at least for mothers) but do not expect it for themselves.

Table 3: Expected annual returns to full-time and part-time experience

| | 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 II.4 - Appendix II.8 we provide evidence that our main result is robust to various changes in the specification. Specifically, 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 percent-1.9 percent, and the difference between the two experience effects is not significant at the 5 percent 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.[15]

# 4 Realized returns to experience

We now contrast the expected returns to experience with realized returns, which we estimate based on longitudinal data from the SOEP core sample. We first provide descriptive evidence on employment and wage trajectories in part-time and full-time employment. Next, we 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 among German women, documenting the shift from non-employment to part-time employment since the 1990s. Non-employment rates of women have decreased strongly since this time, and there appears to be a steady increase in part-time employment, which accounts for most of the increase in overall employment. The full-time employment rates fluctuated over time but did not change much overall between 1990 and 2018. Panel (b) shows a noteworthy regularity that both the level and the increase in part-time employment barely differ by education: part-time shares for women with low, medium, and high education are very similar.

The central driver for female employment is children. In Panel (c), we compare part-time rates between women with and without children by education groups: for mothers, part-time rates are higher among all education groups. The effect of children on part-time shares also features 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 the birth of the youngest child, overall employment decreases. Part-time rates then strongly increase with the age of the child, remaining fairly high even until the child's teenage years.

In Panels (e) and (f), we compare the life-cycle wage profiles of women in part-time and full-time employment. Wages increase with age and education, as one would expect, but with very flat wage-age profiles among low-educated women. The age profile for the highly educated is steep at the beginning of the career and increases

[15]In the additional wave of the SOEP-IS, Wave 2019, which is not used for the main analysis, we elicit expectations about gross hourly wages instead of gross monthly earnings.

moderately after the age of 40.[16] Both overall and within education groups, wage profiles are lower among part-time working women. The figures thus provide suggestive evidence for a part-time experience penalty. However, in this descriptive evidence, we do not yet control for selection effects, endogeneity of experience, or other differences between women in part-time and full-time employment.

## 4.2 Returns to experience: reduced form evidence

To estimate the realized returns to education, we specify a wage equation similar to Equation (1) but where the *actual* years of experience affect hourly wages:

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

Here, $\omega_{it}$ captures the hourly wage and $E_{it}^{Full}$ and $E_{it}^{Part}$ years of experience in full-time and part-time work, respectively, while $\mu_i$ is an unobservable individual fixed effect and $\epsilon_{it}$ an i.i.d disturbance.[17] To account for the endogeneity of accumulated experience and for selection into part-time and full-time employment (in addition to the use of individual fixed effects), we employ a control function approach similar to Blundell et al. (1998) and use time variations in the tax and transfer system period as instruments. Haan & Prowse (2023) show that multiple reforms of the tax and transfer system in Germany after the country's reunification in 1990 introduced variations in the marginal tax rates that vary by pre-tax earnings. In our analysis, we follow Costa Dias et al. (2018) and simulate the net household income in all three employment states: out-of-work, part-time employment, and full-time employment. We then use the simulated incomes in the three states and the number and age of children present in the household as instruments to construct our control functions.[18]

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

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

We estimate the wage equations separately for women with low, medium, and high education. Table 4 includes the estimates with and without control functions. The specifications of the control functions and the estimation results are relegated to Appendix III.

We find closely similar patterns in all specifications and for all education groups: in each case, the realized returns to full-time experience are considerably larger than for part-time experience. The wage elasticity with respect to experience in full-time work lies in the range of 0.09-0.1 for low-educated women (i.e. an increase in the years of experience of 10 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 lies in the range of 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 document a penalty for part-time experience, confirming the results from the UK (Blundell et al. (2016)) for the case of Germany. For low-educated women, the difference is smaller but still statistically significant.[19] In Appendix III, we show that our results are robust to changes to

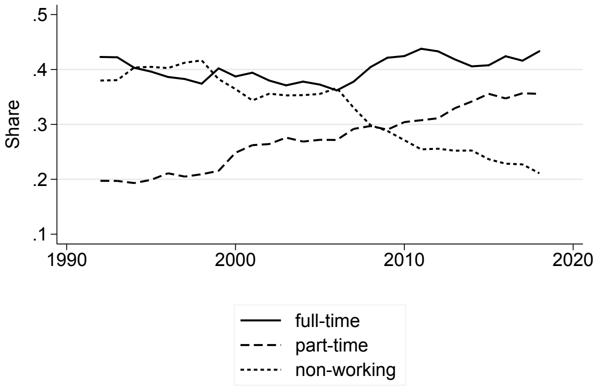
[16] Blundell et al. (2016) report a very similar pattern for the UK.

[17] Because of the log transformation of experience, we add one year of experience to $E_{it}^{Full}$ and $E_{it}^{Part}$, allowing us to include also women with no experience in either full-time or part-time.

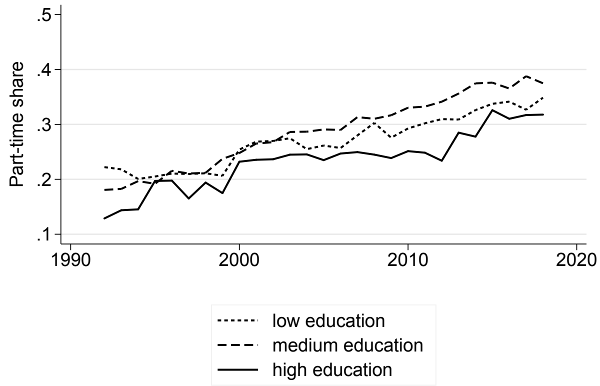
[18] For a similar procedure, see Hammer (2020).

[19] This, too, is consistent with the findings of Blundell et al. (2016)), who report that returns to full-time experience are lower for the low educated.

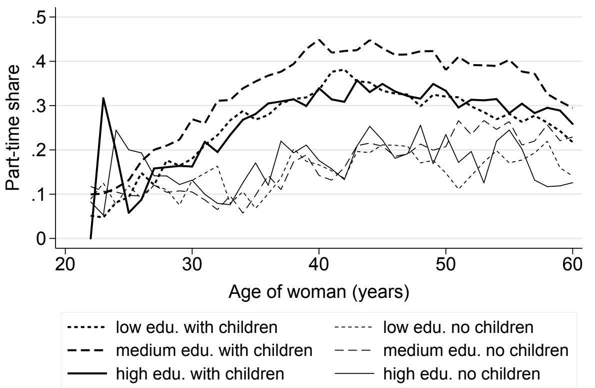
(a) **Employment shares**



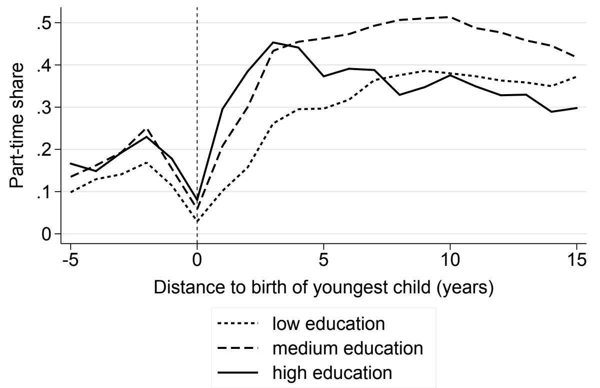

(b) **Part-time employment by education**



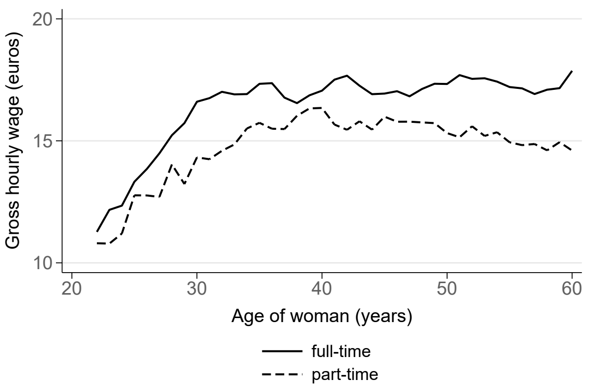

(c) **Part-time employment across the life cycle**




(d) **Fertility and part-time employment**




(e) **Wage trajectories and part-time employment**




(f) **Wage trajectories by education**


Figure 2: Employment and wages of German women 1992-2018

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

Table 4: 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:* Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, SOEP v35. All estimations include a fixed effect and, in addition, an indicator for living in Eastern Germany. The control functions account for selection into employment ($\lambda^e$), selection into full-time employment ($\lambda^h$), and endogeneity of experience in full-time employment ($\lambda^f$) and in part-time employment ($\lambda^p$).

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, finding 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. 2018) and for Germany (Hammer 2020).[20] Also consistent with these two latter studies, our estimation results with and without control functions are quite similar to each other. This suggests that controls for time-invariant, person-specific differences via fixed effects capture selection effects and the endogeneity of full-time and part-time experience.[21]

Comparing estimates of the realized returns with the corresponding expectations (coefficient in Table 2), we observe a strong belief 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.[22]

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 for labor supply decisions, lifetime earnings, and the welfare effects of policy reforms.

[20]Costa Dias et al. (2018) and Hammer (2020) focus on wage growth and account for human capital depreciation when analyzing returns to experience.

[21]Pooled OLS regressions without fixed effects do not account for selection and endogeneity lead to very different results, see Table SWA.14.

[22]While the SOEP-core analysis constitutes a look into the past, the beliefs we elicit are projections into a yet unrealized future. However, it is highly unlikely that this can cause the belief bias we observe. First, we note that wages in the SOEP core analysis adjusted for time-trends and inflation as described in Appendix Appendix I.2. And second, the patterns in reported expectations suggest that perceptions and full-time experience remuneration observed in the SOEP core are closely aligned. Heuristically, there is no reason to believe that respondents expect a structural break in the returns to part-time that would not affect full-time returns at the same time.

# 5 Structural analysis

For a better understanding of the implications of belief biases, we develop and estimate a dynamic life-cycle model of female employment. This allows us to analyze the dynamic effects of the biases in two distinct ways. First, we use the model to quantify the effects of the biases on factual economic outcomes like employment, lifetime earnings, and welfare. We then leverage the model to evaluate the effect of the bias on the impact of a counterfactual policy reform that increases incentives for full-time employment: replacing joint taxation with individual taxation.

## 5.1 Overview of the model

The model is a smaller version of Blundell et al. (2016) and Adda et al. (2017) with modifications specific to our purpose. Our main methodological contribution is that we relax the assumption of rational expectations about the returns to labor market experience in the wage processes. That is, we allow for biased beliefs about the returns to experience in part-time and full-time employment, with the standard assumption of rational expectations being nested as a special case. The model includes the following main features: (i) a forward-looking choice of labor supply between non-employment, part-time, and full-time employment, (ii) a wage process with differential human capital accumulation in part-time and full-time, (iii) a budget constraint featuring relevant elements of the tax and transfer system including child care costs, and (iv) exogenous processes of household formation, fertility, and partner's earnings. We estimate all processes separately by education of the decision-maker (low, medium, and high education) and model the employment choices after the completion of education.[23] We set the last period $\bar{t}$ at age 50. Experience accumulation in the later phases of the career has only minor effects on wages. At the same time, many women start exiting the labor force due to early retirement or informal care of parents and spouses (see e.g. Fischer & Müller (2020). . Focusing on careers up until age 50, we cover the crucial period of experience accumulation over the working life.

Time is discrete with one period in the model qualing a year in real life. Like Blundell et al. (2016), we model household formation, fertility, and the earnings process of the partner outside the structural model. Female employment choices depend on these processes, and the counterfactual policies account for the heterogeneity in these dimensions. In the following, we describe the central elements of the structural model in more detail. The exogenous processes are presented in Appendix IV.

## 5.2 Utility and value function

Each period, a household chooses consumption[24] ($c_t$) and female working hours ($h_t$) according to the following utility function:

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

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 $Z$ summarizes other relevant determinants of the preferences

[23] Women with low and medium education enter the model when 22, while the highly educated enter at age 24 and we account for the initial distribution of central variables including the amount of previously accumulated work experience (for more details, see Appendix IV.1)

[24] We abstract from savings decisions of the household. Thus, the income in the period determines consumption.

for work. Importantly, we control for the presence of children and the age of the youngest child. The parameter vector $\beta_F$ contains the preference for full-time work associated with the presence of children, generally, and for the additional utility effect when the youngest child is aged 0-2, 3-5, or 6-10. In turn, the parameter $\beta_P$ features the corresponding change in the utility from work when the woman works part-time instead of full-time. In the flow utility (4), $c_t/n_t$ represents consumption per adult equivalent, while $\mu$ governs risk aversion and inter-temporal substitution. Following Blundell et al. (2016), we set $\mu$ to $-0.56$. The vector $\theta = (\theta_P, \theta_F)$ has $k$ elements for each employment choice and captures a persistent individual-specific unobserved utility component in part-time and full-time employment. This personal-specific preference heterogeneity is introduced in the form of discrete mass points. The individual type $k$ is associated with a person-specific preference for full-time work $\theta_F$ and a person-specific preference for part-time work $\theta_P$.

Households maximize the sum of expected lifetime utilities, 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 $\delta$ to 0.98.

## 5.3 Budget constraint

Households maximize the value function subject to their budget constraint

$$c_t = h_t w_t + \tilde{w}_t - T(h_t\, w_t, \tilde{w}_t, X_t) + CB - CC. \tag{7}$$

That is, consumption is determined by labor earnings, the net payments into 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 labor income of the partner, $\tilde{w}_t$, if a partner is present. Contributions to and from the tax and transfer system depend on household earnings and the structure of the household. Finally, child benefits and childcare costs are determined by the number and the age of the children, differently between part-time and full-time employment. During the time period 2007-2018 that we use for our estimates, the general structure of the German tax and transfer system only slightly changed.[25] Appendix V provides a detailed description of the tax and transfer system and how its rules are implemented in the structural model.

## 5.4 Wages

Realized hourly wages follow the process:

$$ln\, w_t = \gamma_{s,0} + \gamma_{s,F}\, ln(e_F + 1) + \gamma_{s,P}\, ln(e_P + 1) + \xi_{st} \tag{8}$$

That is, the wage process varies by level of education, s, and depends on the individual experience stock measured in years of full-time and part-time employment, $e_F$ and $e_P$, respectively. To allow for biased beliefs, the following subsection introduces a possible misperception of the education-specific returns to experience, $\gamma_{s,F}$ and $\gamma_{s,P}$. $\xi_{st}$ is a transitory wage shock.

## 5.5 Subjective expectations in the structural framework

The possible bias enters the model via the structural parameter $\alpha_s$ that measures the ratio of expectations about the wage effects of part-time employment and full-time employment, separately for each education level

[25] 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).

$s$. The calculation compares the estimated perceived wage effects of experience, $\zeta_s$ and $\beta_s$ (see Tables 2 and 3) with the corresponding model parameters governing the realized wage effects, $\gamma_{s,F}$ and $\gamma_{s,P}$:

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

The standard assumption of rational expectations is nested in this framework for $\alpha_s = 1$. For any given level of $\alpha_s$, the decision maker's subjectively perceived contribution of the part-time experience stock ($\bar{\gamma}_{s,P}$) is set to

$$\bar{\gamma}_{s,P} = \alpha_s \cdot \gamma_{s,P} \tag{10}$$

and the relevant level of $\alpha_s$ is implied by the parameter estimates of $(\gamma_{s,P}, \gamma_{s,F})$.[26]

## 5.6 Estimation procedure

Estimation proceeds in two stages. In the first stage, we use the SOEP core sample to estimate the exogenous processes of the model: the rates of partner arrival and couple separation, the employment and earnings processes of the partner, and births over the lifecycle. The specifications for the different processes and estimation results are presented in Appendix IV.2 and Appendix IV.3.

In the second stage of the estimation, we use indirect inference to estimate the parameters that govern preferences and wages, as presented in the previous subsections. That is, we specify an auxiliary statistical model that generates two sets of statistics, each based on a different sample: the observed data and a sample that we simulate from our life-cycle model. Parameter values in the life-cycle model are chosen to maximize the proximity between the two sets of statistics. Formally, letting $\omega$ denote the parameters to be estimated in the second stage, the indirect inference estimator of $\omega$ is given by:

$$\widehat{\omega} = \underset{\omega}{\operatorname{argmin}} \left(\widehat{\psi} - \psi(\omega)\right)' \widehat{\Sigma} \left(\widehat{\psi} - \psi(\omega)\right), \tag{11}$$

where $\widehat{\psi}$ denotes the auxiliary parameter estimates based on observed behavior and $\psi(\omega)$ denotes the auxiliary model parameter estimates obtained using a sample simulated from the life-cycle model with parameter values $\omega$. $\Sigma$ is a diagonal weighting matrix.[27]

Our set of moments consists of a mix of conditional choice probabilities and statistics on the wage process (Table 5). The structural parameters of the wage equation (8) are the returns to part- and full-time employment, the constant, and the scale of the wage shock. To identify these parameters, we construct moments based on the hourly wage profiles by education and age. In addition, we employ, analogously to the estimation strategy in Section (4) an individual fixed effect regression to generate statistically meaningful moments for the returns to experience.[28] The scale parameter of the error in the wage equation is then characterized by the moment of the hourly wages' average standard error across individuals in each age-education-experience group.

Given the identified wage parameters, we employ conditional choice probabilities to identify the preference

[26] Note that in this specification, individuals do not update beliefs, as $\alpha_s$ is a constant. This assumption is consistent with the observation that older individuals overestimate wage growth in part-time employment in the same way as young individuals (Table 1). Moreover, previous findings suggest that the part-time penalty is as good as absent in the short-run Manning & Petrongolo (2008*b*), making it plausible that both the existence and the magnitude of the penalty are hard to gauge in a real-life setting, as it requires knowledge of employment and wage over multiple years.

[27] When simulating samples from the life-cycle model, we employ our estimates of the marriage and birth rates and the earnings process of the partner. 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 the SOEP sample are estimated using bootstrapping with household clustering.

[28] For the fixed effect regression, we use the full 1992-2018 sample.

Table 5: Moment functions

| Name | Description |
|---|---|
| Wages (mean) | Education/age-specific wages, in part- and full-time. |
| Wages (variance) | Standard error of wages conditional on education, age, and experience in part- and full-time. |
| Return to experience | Return to experience in full-time and part-time, estimated with individual fixed effects. |
| Employment by education | Education/age-specific labor supply probabilities. |
| Employment women with children | Education/age-specific labor supply probabilities, women with children. |
| Employment women without children | Education-specific labor supply probabilities, women without children. |
| Employment by age | Education-specific labor supply probabilities, separated by children's age ranges. |

*Notes:* Summary of moments by parameter group for which they provide identifying variation. Moment functions are computed based on the observed data and the dataset simulated using the structural model and fixed vector of model parameters.

parameters of part-time, full-time, and non-employment. We calculate age- and education-specific choice probabilities for the different employment states as well as choice probabilities conditional on family characteristics and match these with our simulated sample.

# 6 Structural estimation results

In this section, we present the structural estimation results. We establish that the estimated lifecycle framework supports our findings about experience returns and associated penalties from the analysis in Section 4. Our structural results confirm that part-time work is associated with a sizable penalty in experience accumulation, which is most severe for the highly-educated. Part-time experience penalties, in turn, lead to losses in lifetime earnings. In the following, we present the structural estimation results in detail.

## 6.1 Parameter estimates

The parameters we estimate in our indirect inference procedure can be split into two groups, wage-related parameters featured in Equation 8, and preference-related parameters, associated with Equations Equations 4 and 5.

**Wage process** We presented the estimates of the parameters of Equation 8 in Table 6.

The structural wage process in Equation 8 mirrors the reduced form specification of the wage equation we discuss in Section 4. This allows for comparing our structural estimates and the results obtained using the control function approach. The estimated experience profiles closely replicates the reduced form evidence in Table 4. Returns to full-time experience increase with the level of education. For low-educated women, a 10 percent increase in full-time experience shifts wages by about 0.7 percent. For the medium-educated, the effect is close to 1.6 percent, while for highly-educated women, wages increase by more than 2.1 percent. In line with

Table 6: Wage parameters

| | Education | | | | | |
|---|---|---|---|---|---|---|
| | Low | | Medium | | High | |
| | Coeff | St. Error | Coeff | St. Error | Coeff | St. Error |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept | 2.238 | (0.034) | 2.239 | (0.018) | 2.381 | (0.031) |
| Return to full-time experience | 0.074 | (0.017) | 0.162 | (0.009) | 0.209 | (0.011) |
| Return to part-time experience | 0.050 | (0.015) | 0.053 | (0.007) | 0.061 | (0.011) |
| Standard deviation of error | 0.241 | (0.004) | 0.241 | (0.004) | 0.241 | (0.004) |
| Belief bias $\alpha$ | 1.502 | | 3.510 | | 4.421 | |

*Notes:* SMM parameter estimates of the structural wage process, Equation 8. Standard errors in parenthesis. Intercepts and experience returns by education groups are estimated based on education-specific moment functions. The scale of the transitory wage shock is assumed to be equal for all three education groups.

the reduced-form results, the effect of full-time experience on wages for the highly educated is more than twice as large as for the low-educated.

Additionally, consistent with the reduced-form evidence, the structural analysis points to a stark difference in experience accumulation between full-time and part-time work. The returns to experience from part-time employment are lower for all education groups. A 10 percent increase in part-time experience raises the wage by a factor between 0.5 percent and 0.6 percent. The returns to experience from working part-time only slightly increase with the level of education. Therefore, the gap between full-time and part-time returns strongly differs between the groups. It is largest for the highly-educated (0.148 log points) and smallest for the low-educated (0.024 log points). Thus, the results document a part-time experience penalty that strongly increases with education.

We illustrate the long-run implications of the part-time experience penalty for each education level in Figure 3.

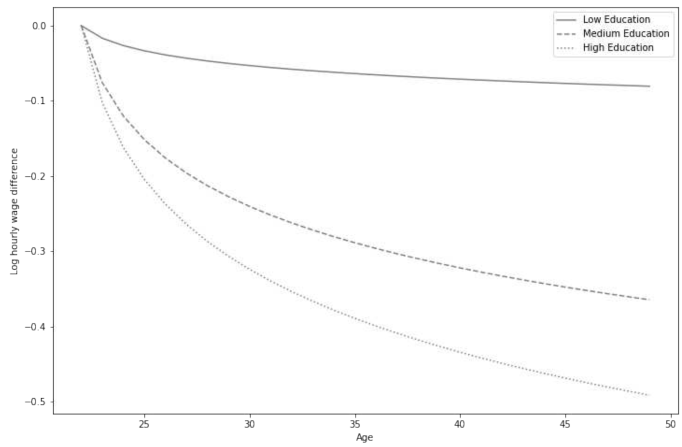



Figure 3: Part-time penalty

*Notes:* The figure shows the log hourly wage differences at each age of part-time work through the life-cycle. To do so, we compare women of all three education groups in two hypothetical scenarios. In the baseline, the woman works full-time from 22 to 50, and in the counterfactual part-time over this age span.

The figure shows how hourly wage trajectories in part-time employment deviate from the full-time employment benchmark, which assumes that individuals work full time throughout. The largest losses appear for women with high education. The part-time wage gap reaches 50 percent at age 50. Part-time experience penalties are also present for women with medium and low education but the associated wage gaps are considerably smaller, about 35 percent and 10 percent, respectively. These wage profiles are in line with the findings of Costa Dias et al. (2018), Paul (2016), and Blundell et al. (2016) who document a long-run part-time experience penalty close to 50 percent for British women with university degrees. They also show considerably lower part-time penalties for women with high school and secondary education.

Finally, we turn to the bias in expectations (last row in Table 6). The structural parameters that determine the returns to full-time and part-time experience and the estimated expected returns to full-time and part-time employment from Section 3.4 yield the bias parameters $\alpha_s$ as specified in Equation 9. The bias is smallest for women with low education at 1.52, women with medium education are at 3.51, while women with high education are at 4.22. This difference by education is not related to the expected returns to experience, which are similar for the different groups (see Table 3) but they are explained by the markedly higher realized returns to experience in full-time employment for women with medium and high education.

**Preferences** In Table 7, we present the estimates of the structural parameters featured in Equations 4 and 5 that describe preferences in our lifecycle framework.

Table 7: Preference parameters

| | Utility Paramters | | | |
|---|---|---|---|---|
| | Full-time Employment | | Part-time Employment | |
| | Coeff. | St. Error | Coeff | St. Error |
| | (1) | (2) | (3) | (4) |
| Mother, High Education | 0.576 | (0.015) | -0.582 | (0.021) |
| Mother, Medium Education | 0.576 | (0.015) | -0.609 | (0.017) |
| Mother, Low Education | 0.645 | (0.016) | -0.617 | (0.019) |
| No children, High Education | 0.195 | (0.029) | -0.143 | (0.028) |
| No children, Medium Education | 0.263 | (0.018) | -0.218 | (0.019) |
| No children, Low Education | 0.441 | (0.173) | -0.406 | (0.178) |
| Child aged 0-2 | 0.273 | (0.021) | -0.000 | (0.021) |
| Child aged 3-5 | 0.190 | (0.013) | -0.022 | (0.013) |
| Child aged 6-10 | 0.117 | (0.013) | -0.021 | (0.013) |
| | Unobserved Heterogeneity in Disutility of Work | | | |
| | Full-time Employment | | Part-time Employment | |
| Unobserved type 1 | -0.598 | (0.013) | -0.134 | (0.017) |
| Probability Type 1 | 0.575 (0.031) | | | |

*Notes:* SMM estimates of preference parameters, Equation 5. Standard errors in parenthesis. Coefficients for groups of individuals with certain observed characteristics are estimated based on group-specific moment functions. The unobserved component of the disutility of work, $\theta$, is assumed to be not group- but individual-specific.

For all groups, the coefficients of full-time employment imply that women experience a certain degree of disutility when working full-time.[29] Disutility is higher for women with children. The presence of young children further decreases the utility of working full-time while the strongest effect is for children aged 0-2. Both among women with and women without children, the utility cost of working full-time is highest for the low-educated and lowest for the highly-educated.

[29] As $\mu$ in the flow utility, Equation 4 takes on a negative value, positive values in $\beta$ translate into a lower utility.

As specified in Equation 5, the coefficients which enter the equation additionally if the individual chooses to work part-time quantify the difference in disutility associated with working part-time instead of full-time. The negative sign of the part-time coefficients signifies that working part-time has lower utility costs than working full-time. This is the case for all groups and the parameters across education groups are similar. Part-time employment is associated with even lower disutility of work for mothers with young children. The age of children has only a minor effect. The reduction in the utility cost between full-time and part-time employment is small and approximately equal for mothers of children aged 3-5 and 6-10 and close to zero for mothers of children aged 0-2.

Finally, we estimate the utility contribution of the individual-specific persistent preference type and the probability that individual $i$ is of type $p \in \{I, II\}$. Individuals of type I face lower disutilities of work, both in full- and part-time work. They are estimated to constitute about 58 percent of the population.

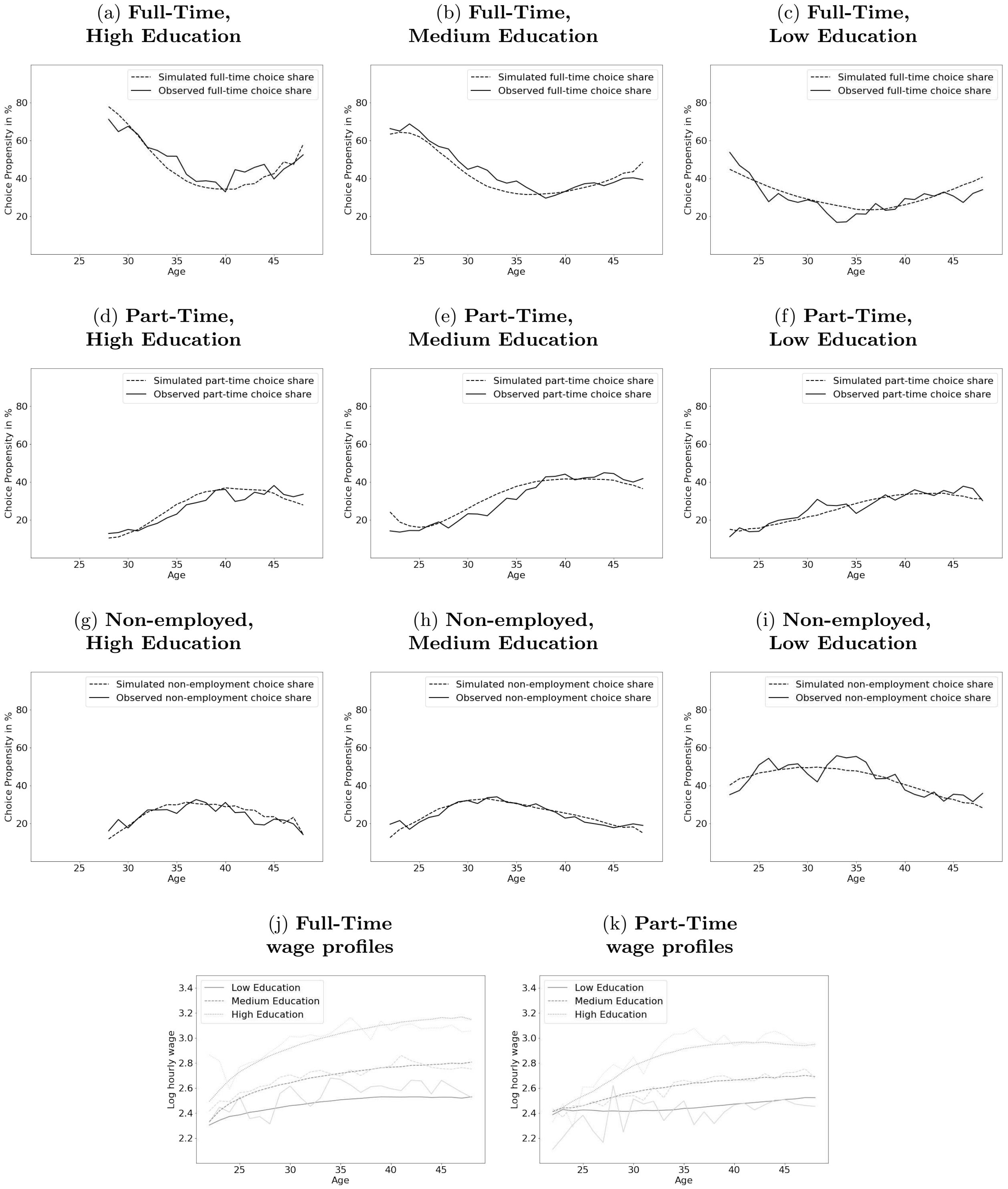
**Elasticities** To see the implications of the estimated structural parameters for employment behavior, we derive labor supply elasticities for all women and by education and age groups (Table 8). We calculate elasticities by increasing gross hourly wages at each age by 1 percent and simulating the change in labor supply. The extensive margin summarizes the change in the share of the population working either part- or full-time. The intensive margin measures the percentage change in the working hours of women who already worked before the wage increase. According to our estimates of the structural model an increase in wages by 1 percent leads to an increase in the participation (extensive) of women by 0.36 percentage points. We find no strong age pattern but we do find differences by education. Women with low education react with an average elasticity of 0.42, which is stronger than for women with medium or high education. For the intensive margin, elasticities are smaller. Overall, a change in wages by 1 percent would lead to an increase in working hours by 0.18 percent. The pattern by education is less clear than for the extensive margin, but we find more variation by age. Generally speaking, our elasticities are close to estimates in the previous literature. For example, in their analysis of UK data, Blundell et al. (2016) find an extensive elasticity of 0.475 and an intensive elasticity of 0.21, with educational differences that are analogous to ours.

Table 8: Marshall Elasticities

| | Extensive | | | | | | Intensive | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | 25-29 | 30-34 | 35-39 | 40-44 | 45-49 | All | 25-29 | 30-34 | 35-39 | 40-44 | 45-49 |
| All women | 0.36 | 0.35 | 0.38 | 0.36 | 0.36 | 0.35 | 0.18 | 0.05 | 0.16 | 0.20 | 0.24 | 0.24 |
| Low Education | 0.42 | 0.41 | 0.38 | 0.41 | 0.41 | 0.48 | 0.21 | 0.11 | 0.20 | 0.27 | 0.27 | 0.20 |
| Medium Education | 0.35 | 0.37 | 0.39 | 0.37 | 0.35 | 0.28 | 0.16 | 0.01 | 0.17 | 0.20 | 0.20 | 0.20 |
| High Education | 0.29 | 0.24 | 0.34 | 0.25 | 0.30 | 0.32 | 0.20 | 0.08 | 0.12 | 0.11 | 0.31 | 0.38 |

*Notes:* Extensive margin is the percentage point change in labor supply in response to a 1 percent increase in gross earnings. Intensive margins are calculated conditional on employment

**In-sample fit** Finally, we show that the estimated life-cycle profiles of employment and wages are very similar to the observed counterparts. In Figure 4, we document the education-specific age profiles of the three employment states. For each group, the model replicates quite closely the decline in full-time employment at ages when women tend to have young children and the increase at higher ages. The model further replicates the shares in part-time employment, which increase in age, and the shares in non-employment, which are markedly higher for women with low education. At the bottom of Figure 4, we turn to the wage profiles in part-time and full-time employment. The estimated wage processes show a relatively flat wage profile for the low educated. Wages are higher for medium- and highly-educated women and their age profiles are steeper, too. This is particularly prominent for the highly-educated and is also replicated by the model.




(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) **Non-employed, High Education** (h) **Non-employed, Medium Education** (i) **Non-employed, Low Education**

(j) **Full-Time wage profiles** (k) **Part-Time wage profiles**

Figure 4: Life-cycle choice and wage profiles

*Notes:* These figures show the in-sample fit of the model. Solid lines depict the simulated wages, while dashed show the observed wage profiles.

# 7 Counterfactual simulations

In the final section of the analysis, we leverage the structural model to understand the effects of biased beliefs for employment, earnings, and welfare via counterfactual simulations. Moreover, we quantify how a tax reform that incentivizes full-time employment can change employee behavior and lifetime earnings and how the belief bias affects the implications of this reform.

## 7.1 De-biased beliefs

In the first simulation, we analyze how the incentives to engage in part-time employment change when individuals in the model make choices based on correct expectations about the returns to experience in part-time employment. We quantify the effect of de-biasing on employment, labor earnings, and welfare. To this end, we simulate a hypothetical scenario with de-biased expectations about the returns to experience and compare it to the baseline scenario with biased beliefs. In the scenario with de-biased expectations, we set the bias parameter $\alpha_s$ =1 for all education groups $s$, thereby assuming that all individuals have rational expectations about the realized returns to experience, as estimated in the wage process of the structural model. All other structural parameters are kept as in the baseline scenario.

Table 9: Life-cycle effects of rational beliefs

| | | | Education | | | | | |
|---|---|---|---|---|---|---|---|---|
| | All | | Low | | Medium | | High | |
| | Bias | De-bias | Bias | De-bias | Bias | De-bias | Bias | De-bias |
| Full-time employment | 39.71 | 42.92 | 30.43 | 30.66 | 40.51 | 44.08 | 51.61 | 58.35 |
| | [3.21] | | [0.23] | | [3.58] | | [6.74] | |
| Part-time employment | 30.40 | 24.17 | 27.57 | 26.81 | 33.75 | 26.57 | 25.92 | 13.90 |
| | [-6.23] | | [-0.76] | | [-7.18] | | [-12.01] | |
| Non-employment | 29.89 | 32.92 | 42.00 | 42.53 | 25.74 | 29.35 | 22.48 | 27.75 |
| | [3.03] | | [0.53] | | [3.61] | | [5.27] | |
| Lifetime earnings | 1.33 | | -0.25 | | 1.14 | | 2.62 | |
| Welfare measure | 0.62 | | 0.01 | | 0.68 | | 1.66 | |

*Notes:* We simulate individuals from age 25 to 49. Employment shares are given in percentage points. The difference between the baseline and the de-biased scenario is given in parentheses. Lifetime income is presented as the percentage change of the average lifetime income. The welfare measure is given as the percentage consumption change per period, i.e. $\gamma$ from Equation (12).

In the first part of Table 9, we compare the shares in the three employment states between the scenarios with bias and without bias, calculated as averages over the entire lifecycle. In addition we present in square brackets differences between the scenarios in percentage points. Overall, the effect of de-biasing is sizable: it reduces part-time employment, on average, by 6.23 percentage points. However, de-biasing does not lead to an increase in the overall employment rate because women move to non-employment and into full-time employment. About half of the women with changed status (3.21 percentage points) choose to work full-time, whereas the other half (3.03 percentage points) moves to non-employment. Disutility for work explains this pattern: in the subjectively expected future life of a biased decision maker, the inflated returns to part-time experience compensate for the disutility. In contrast, individuals in the de-biased scenario realize that part-time returns are low, thusly the effect of disutility for work dominates.

Notably, the employment effects of de-biasing increase with education, consistent with the education-specific size of the bias we reported in Table 6. Part-time employment among women with high education decreases by about 12 percentage points on average while the reduction for low-educated women is less than one percentage point. Moreover, the substitution pattern also differs by education. De-biasing mostly leads to a move into non-employment for the group with low education. In contrast, most women with high education transition from part-time to full-time employment. For the medium-educated, the pattern is similar to the full-population: about half of those who change their employment transition into full-time employment and the other half into non-employment.

In the second part of the table, we turn to the implications for lifetime earnings and welfare. De-biasing leads to higher income inequality, as its wage effects differ by education and amplify existing earnings gaps. For the entire sample, lifetime earnings increase by 1.33 percent. This increase is mainly driven by the highly-educated, whose income increases by 2.62 percent. The low-educated even experience a loss of income since the effect on non-employment dominates.

For the welfare analysis, we follow Low et al. (2010) who measure the welfare effects by the consumption variation that is welfare equivalent to the change from one scenario to the other. Formally, let A denote the de-bias environment and let B denote the baseline scenario with the bias. The welfare value of scenario A is denoted by $\gamma_A$ and solves $V_B(\gamma_A) = V_A(0)$, where

$$V_e(\gamma) = \mathbb{E}\left[\sum_{\tau=t_i}^{\bar{t}} \delta^\tau u(c_\tau(1+\gamma), h_\tau, \theta, Z_\tau)\right], \text{for} \in \{A, B\}. \tag{12}$$

In the above equation, $t_i$ denotes the time when the decision maker joins the model, and the expectation is with respect to all exogenous processes and the wage shock. Therefore $\gamma_A$ describes the relative increase in per-period consumption to equal the average discounted utility in the counterfactual scenario.[30]

De-biasing leads to welfare gains for all groups. This is because the welfare measure accounts not only for monetary gains and losses but also for the changes in the dis-utility of employment. Welfare increases on average by an equivalent of 0.62 percent of lifetime consumption. Like the previous results, the welfare effects differ by education. Welfare gains are highest for the highly-educated. They see an increase of 1.66 percent of life-time consumption, for women with medium education the effect is clearly lower (0.68 percent) and for low-educated women the effect is negligible (0.01 percent).

Overall, the simulations show that biased beliefs about the returns to experience have ambiguous consequences for employment and lifetime earnings for women. Importantly, in the aggregate, de-biasing would not lead to an increase in employment. Thus, a hypothetical policy that provides information to correct the biased beliefs would be ineffective in increasing female employment and their lifetime earnings. To achieve this policy goal, further policy reforms would be necessary. We now turn to the analysis of such a reform and its interaction with biased expectations.

## 7.2 Tax reform: Individual taxation

We consider the employment and earnings effects a prominent reform proposal in Germany that would increase the incentives for full-time employment: the introduction of individual taxation instead of joint taxation with full income splitting for couples, see e.g. OECD (2023). Building on the analysis in the previous subsection, we compare the employment and earnings effects in the two scenarios introduced there.[31] That is, we consider the implications of the tax reform twice: in the baseline scenario with biased beliefs and the scenario with de-biased beliefs. The second simulation implements, thus, a combination of de-biasing and the introduction of the tax reform. While such a scenario is rather hypothetical, its comparison to the tax reform in the baseline scenario allows answering how the bias affects the employment and earnings effects of the reform.

In Germany, households of married couples are taxed jointly with full income splitting, see Appendix V. This system imposes a higher marginal tax rate on the secondary earner in the household, i.e., the partner with

[30] In this calculation, the consumption adjustment $\gamma_A$ is implemented ex-post and, therefore, does not affect behavior.

[31] The reform is not revenue neutral. Therefore, we abstract from a detailed welfare comparison.

lower earnings, relative to individual taxation. Previous studies document that joint taxation induces strong disincentive effects for full-time employment for the secondary earner. Moreover, as households with high taxable income and unequal distribution of earnings within the couple have a higher advantage from income splitting, joint taxation has important distributional implications, see, e.g., Bick & Fuchs-Schündeln (2017*b*) or Bach et al. (2020). Specifically, it favors households in which the spouse with higher earnings, typically the husband, works full-time and the other spouse, normally the wife, is not employed or works part-time. Even a short part-time spell can have strong permanent effects because the relative loss in the wife's human capital increases the disparity in the two spouses' income levels further – especially for the highly educated (Goldin 2021) – and the incentive effect of joint taxation thus increases over time. Introducing individual taxation that would tax both spouses according to their individual taxable income incentivizes women who are in general the secondary earner in the household to work more.

Our simulations show that, indeed, the introduction of individual taxation would strongly increase employment and earnings over the working life. Table 10 shows the effects on women's employment shares and lifetime income in the baseline scenario that includes biased beliefs about the returns to experience. We find that, on average, the policy reform reduces the share of non-employment by 3.06 percentage points over women's working lives. Overall the share of moving from non-employment into part-time employment is larger than the share of moving from non-employment to full-time employment (2.75 versus 0.31 percentage points). Note that part-time employment appears attractive for two reasons. 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 relative to full-time employment are not incorporated, rendering this choice more attractive. Still, the reform would lead to a meaningfully change in lifetime earnings. Overall we find that the reform increases lifetime earnings by 2.78 percent with positive effects for all education groups. While the effect on non-employment is similar across the different educational groups, the relative increases in part-time and full-time employment differ strongly by education group. We see the strongest increase in full-time employment for highly-educated women (1.17 percentage points). For the low educated, the corresponding move to full-time is only 0.25 percentage points and for medium educated the effect is even smaller. In contrast the increase in part-time employment is strongest for the low educated.

Table 10: Life-cycle effects of individual taxation

| | | Education | | |
|---|---|---|---|---|
| | All | Low | Medium | High |
| Full-time employment | 0.31 | 0.25 | 0.01 | 1.17 |
| Part-time employment | 2.75 | 3.09 | 2.85 | 1.99 |
| Non-employment | -3.06 | -3.34 | -2.86 | -3.16 |
| Lifetime earnings | 2.78 | 3.37 | 2.18 | 3.44 |

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

The effects on lifetime earnings are even larger in the scenario in which we consider the joint effects of de-biasing and the introduction of individual taxation, and the pattern of the employment effects is very different. In contrast to the effect when beliefs are biased, here, individual taxation implies a 3.85 percentage point increase in full-time employment and a 0.31 percentage point decrease in non-employment. Similar to the simulation with de-biased expectations (Table 9), part-time employment is reduced. For all women, we find a reduction of over three percentage points. Considering effect heterogeneity by education, we find that the effects on employment and on entering full-time employment, in particular, are highest for the highly-educated. For this group we see an increase in full-time employment by more than 8.8 percentage points. The effects for medium educated point in the same direction but they are smaller. Interestingly, for the low educated we still find a sizable increase in part-time employment (2.45). This is consistent with the smaller part-time experience penalty and the smaller estimate of biased beliefs for this group (see Table 6).

Table 11: Life-cycle effects of individual taxation and rational beliefs

| | | Education | | |
|---|---|---|---|---|
| | All | Low | Medium | High |
| Full-time employment | 3.85 | 0.48 | 3.87 | 8.85 |
| Part-time employment | -3.53 | 2.45 | -4.24 | -10.70 |
| Non-employment | -0.31 | -2.93 | 0.37 | 1.84 |
| Lifetime earnings | 4.91 | 3.16 | 4.07 | 7.44 |

*Notes:* Employment effects are presented in the 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 explore 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, earnings, and welfare for women in Germany. We document that expectations about wage growth in part-time employment are severely upward biased. In particular, we elicit expectations in a representative survey and the survey responses imply that individuals do not expect any form of part-time penalty. Importantly, we show that this finding holds for different heterogeneous groups which differ by education, employment state, or age.

In contrast, reduced form estimations, which account for selection effects and the endogeneity of accumulated experience in part-time and full-time employment, show that wage growth rates in part-time work are close to zero but significantly larger for full-time employment. This part-time experience gap strongly increases with education. Thus, this empirical pattern with is in line with the previous results for Germany and other countries contradicts the elicited subjective expectations of women.

In the last part of this paper, we develop a structural life-cycle model of female employment and earnings to show how subjective expectations determine labor supply choices and dynamically translate into labor market outcomes. The structural model replicates the findings of a sizeable part-time experience penalty and the education pattern. Moreover, leveraging the elicited expectation data we identify education-specific bias parameters which reconcile the difference between the subjective beliefs and the empirical experience-wage profile. In counterfactual simulations we quantify the employment, earnings and welfare effects of biased beliefs. The bias translates into an increased propensity of part-time employment by about six percentage points, on average, across all women. While about half of the women react to a hypothetical de-biasing by moving from part-time to non-employment, the other half switch from part-time to full-time work. Thus, overall, employment would not increase. We find again an important education gradient which suggests that highly-educated women see the strongest increase in full-time employment, life-time earnings and welfare.

Finally, we study how policy reforms could increase labor supply and the share of full-time employment of women. We consider a tax reform that is widely discussed in Germany: abandoning joint taxation of couples.

The reform would increase overall employment and the share of full-time employment. The effects would be even strong without the bias about the part-time penalty. In this scenario part-time employment is less attractive and, thus, the reform would induce a larger increase in full-time employment with sizable implications for lifetime earnings.

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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 Additional sample restrictions in the structural analysis

This section presents additional sample restrictions 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 the employment state, experience, or age of the youngest child is missing but include women with missing wage information if the employment state is non-missing.

## Appendix I.2 Variable description

We define *employment* based on annual measures of self-reported employment status[32], 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 the 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 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[33] 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.3 Comparison of SOEP and SOEP-IS

In this Appendix, we provide evidence that the samples from the SOEP core 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.

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[32] 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, and second because, in eliciting wage expectations, we use filters in the SOEP-IS questionnaire that are based on self-reported employment status.

[33] Comparative Analysis of Social Mobility in Industrial Nations

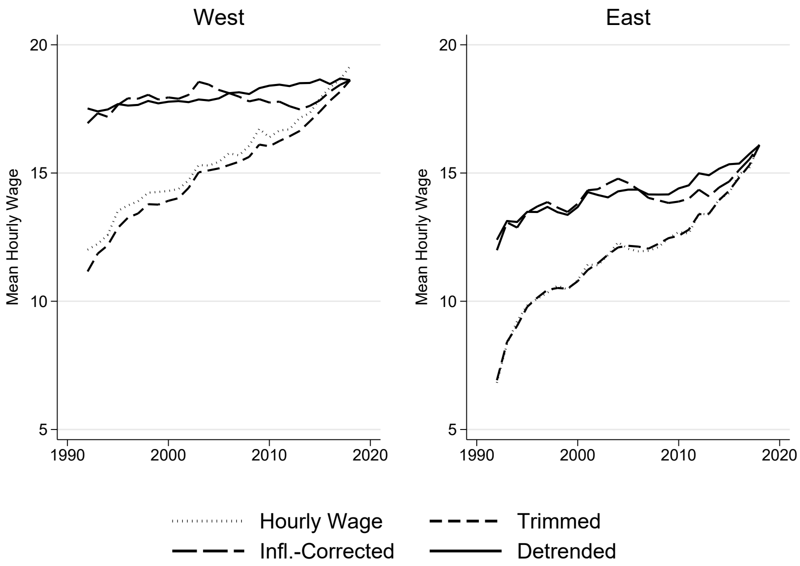



Figure SWA.1: Wage evolution and detrending

*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.

| | 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 | | |

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

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

# Appendix II: Wage expectations

In this Appendix, we provide details about the survey design, and show various robustness checks for the analysis of the expected returns to experience in part-time and full-time employment.

## 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 the 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.[34]

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 the 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.

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

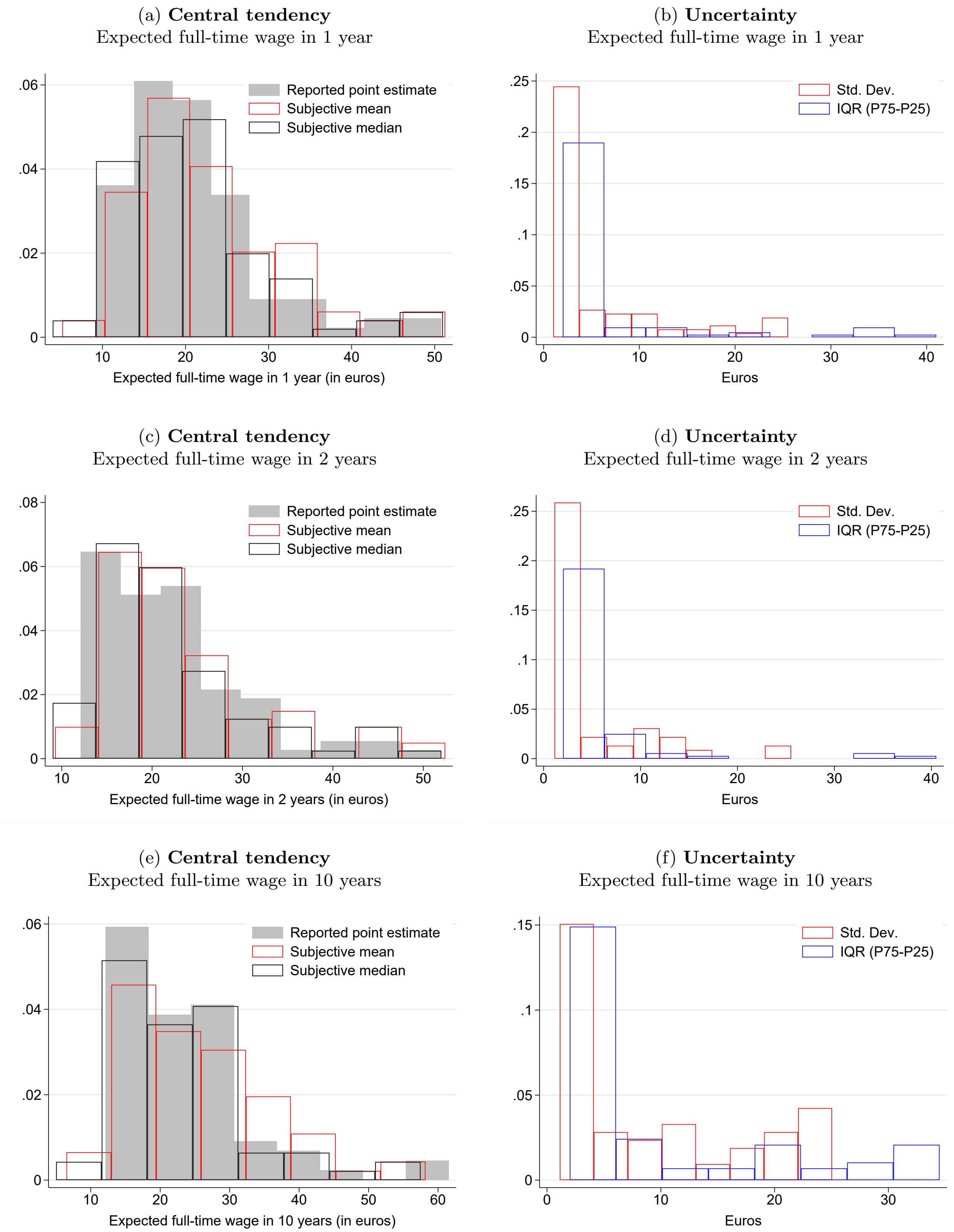



Figure SWA.3: Distribution of central tendency and uncertainty in full-time wage expectations

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

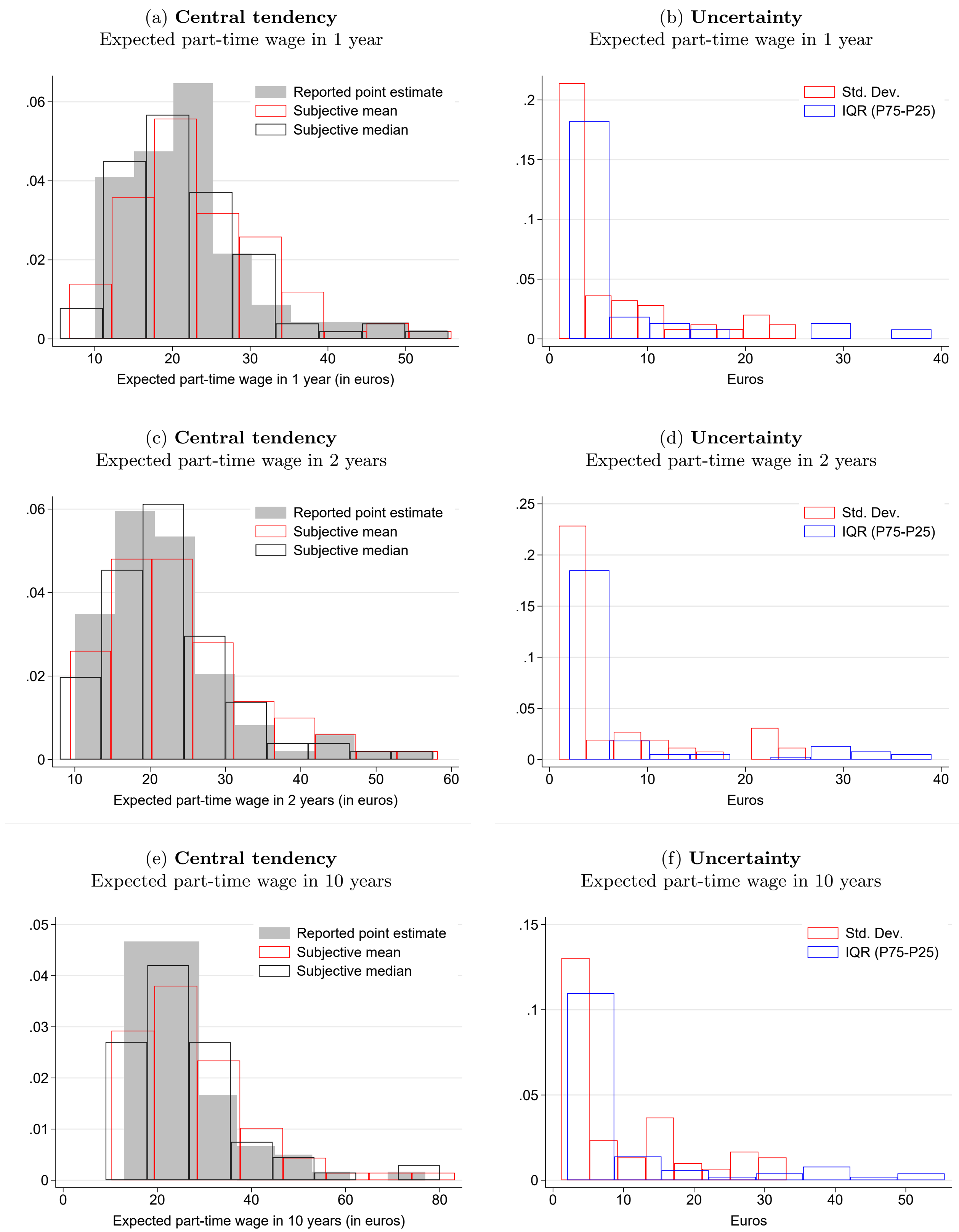



Figure SWA.4: Distribution of central tendency and uncertainty in part-time wage expectations

*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

| | 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 Robustness: Specification based on a balanced panel

Table SWA.4: Expected annual returns to full-time and part-time experience

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Log experience in full-time | 0.080*** | 0.081*** | 0.068*** | 0.068*** |
| | (0.006) | (0.006) | (0.005) | (0.006) |
| Log experience in part-time | 0.096*** | 0.093*** | 0.089*** | 0.087*** |
| | (0.009) | (0.009) | (0.008) | (0.008) |
| Difference part-/full-time | 0.015* | 0.012 | 0.021*** | 0.020** |
| | (0.008) | (0.008) | (0.007) | (0.008) |
| N | 1,464 | 1,332 | 1,952 | 1,776 |
| Estimation | FE | POLS | FE | POLS |
| Incl. t=0 | no | no | yes | yes |

*Notes:* SOEP Innovation Sample (2016-2018). Balanced panel of women with valid responses to all 8 expectation questions. 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.

## Appendix II.6 Additional results: Heterogeneity in earnings expectations

Table SWA.5: Heterogeneity in Expected Returns to Experience

| | Log full-time experience | | Log part-time experience | | Mean Difference ($\beta$) | | N |
|---|---|---|---|---|---|---|---|
| | $\beta$ | s.e. | $\beta$ | s.e. | $\beta$ | 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.7 Robustness: Specification with real wages

Table SWA.6: 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.8 Robustness: Belief elicitation based on hourly wage information

Table SWA.7: 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 variations 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[35] 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 ($\lambda^e$), selection into full-time work ($\lambda^h$) and endogeneity of experience in part-time employment ($\lambda^p$), and endogeneity of experience in full-time employment ($\lambda^f$).

## Appendix III.1 Selection into employment

Table SWA.8: 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:* Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. SOEP v35, estimated by Probit. Sample includes women who work and who do not work. All models include a dummy for Eastern Germany.

[35] We follow Costa Dias et al. (2018) and regress the simulated income on the 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.

We estimate the selection into employment by probit, using the number of children and simulated income in non-employment as instruments (see Table SWA.8).

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 for full-time employment is explained by the number of children in different age groups and the woman's own age (Table SWA.9). In addition, we construct instruments based on the residualized simulated income in part-time and full-time employment[36]: the simulated income in full-time work and the difference in 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. (2018), 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 employment (Table SWA.10) and part-time employment (Table SWA.11) 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.

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

Table SWA.9: 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:* Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

Table SWA.10: 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:* Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

Table SWA.11: 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:* Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

## 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. We also show estimates based on OLS regressions without individual fixed effects to highlight the importance of controlling for individual fixed effects to account endogeneity.

Table SWA.12: 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 | 0.105*** | 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:* Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, SOEP v35. All estimations include a fixed effect and an indicator for living in Eastern Germany. The control functions account for selection into employment ($\lambda^e$), selection into full-time employment ($\lambda^h$), and endogeneity of experience in full-time employment ($\lambda^f$) and in part-time employment ($\lambda^p$).

The central findings of this specification are quite similar to the results of the main specification. Adding an indicator for part-time work in the current period hardly affects the point estimates of the returns to part-time and full-time experience (Table SWA.12). Consistent with previous studies for Germany, see e.g. Paul (2016) or Schrenker (2020*b*) 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.[37]

In Table SWA.13, 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.[38] Thus, the central finding of a part-time experience penalty does not depend on the functional form of the wage equation.

In Table SWA.14, we show estimates based on OLS regressions without individual fixed effects.

[37]Schrenker (2020*b*) provides an overview of the international literature, which finds mostly small to no effects of the current employment state on wages for female workers.

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

Table SWA.13: Returns to Full-Time and Part-Time Experience

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

Table SWA.14: 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 | 0.094*** | 0.095*** | 0.125*** | 0.137*** | 0.092*** | 0.092*** |
| | (0.006) | (0.008) | (0.005) | (0.006) | (0.009) | (0.012) |
| Log experience in part-time | 0.009* | -0.047*** | 0.013*** | -0.054*** | 0.002 | -0.055*** |
| | (0.005) | (0.009) | (0.004) | (0.007) | (0.008) | (0.017) |
| $e$ | | -0.221*** | | -0.164*** | | -0.334*** |
| | | (0.027) | | (0.027) | | (0.055) |
| $h$ | | 0.102*** | | 0.134*** | | 0.276*** |
| | | (0.021) | | (0.015) | | (0.031) |
| $f$ | | 0.000 | | 0.001 | | -0.003 |
| | | (0.001) | | (0.001) | | (0.002) |
| $p$ | | 0.011*** | | 0.015*** | | 0.009** |
| | | (0.001) | | (0.001) | | (0.004) |
| Constant | 2.323*** | 2.469*** | 2.456*** | 2.475*** | 2.836*** | 2.861*** |
| | (0.016) | (0.027) | (0.012) | (0.015) | (0.022) | (0.029) |
| Prob > F ($lnE^{Full} = lnE^{Part}$) | 0.0000 | 0.000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| N | 23,696 | 23,696 | 48,534 | 48,534 | 19,968 | 19,968 |

*Notes:* Standard errors clustered at the person level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, SOEP v35. OLS estimates with a control variable for living in Eastern Germany. The control functions account for selection into employment ($\lambda^e$), selection into full-time employment ($\lambda^h$), and endogeneity of experience in full-time employment ($\lambda^f$) and in part-time employment ($\lambda^p$).

# Appendix IV: Initial conditions and exogenous processes

## Appendix IV.1 Initial conditions

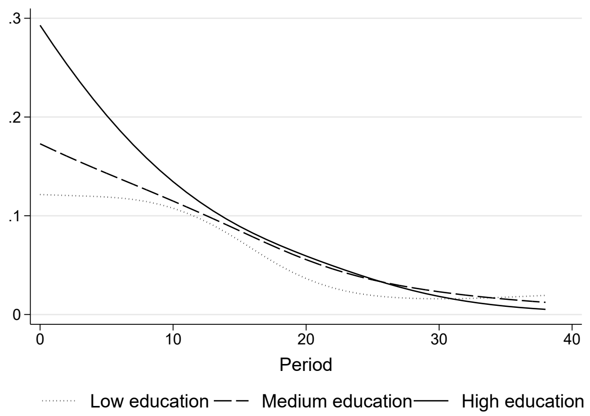
Women enter the model at age 22 if they are low- or medium-educated and at age 24 if they are highly educated. To set the initial conditions of the exogenous variables, we use education-specific empirical shares to estimate the probability that at the age they enter, (i) a woman already has a partner, (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 Partner arrival, separation and partner earnings

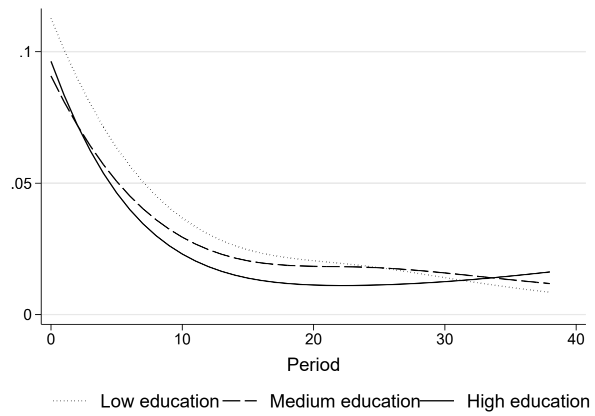
For women aged 22-60, we estimate the probability that a single woman finds a partner in a given year separately by education (low, medium, or high) using logistic regressions with a cubic polynomial in female age. Analogously, we estimate the probability that a woman who had a partner in the previous 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

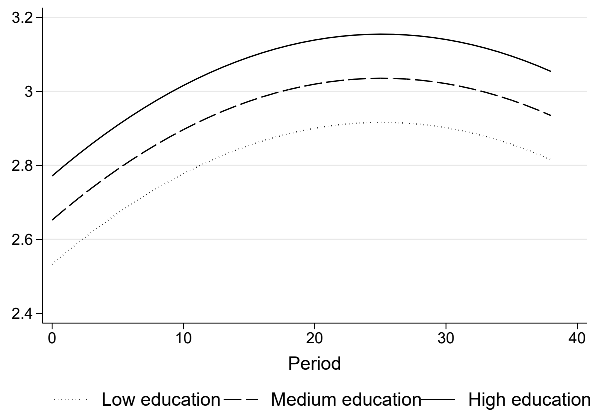
To estimate annual birth probabilities, we estimate education-specific logistic regressions of childbirth as a function of female age up to a third-order polynomial for women in child-bearing age until age 42. We set birth probabilities to zero for women above age 42.




(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

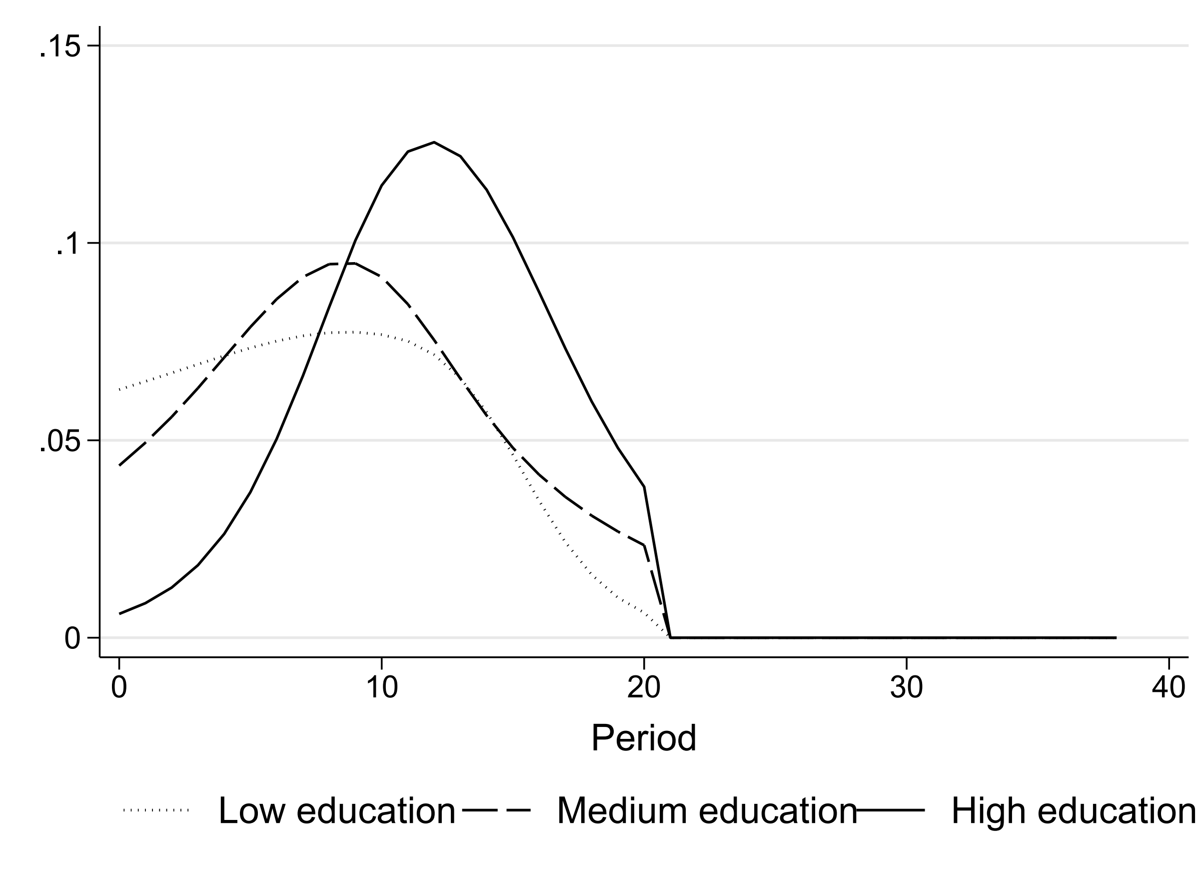



Figure SWA.6: Annual birth probabilities

## 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 7). 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.

### 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 percent on individuals' labor earnings below a cap of 63,000 euros per year.[39]

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.[40] 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 percent of the household's tax liability, excluding social security contributions.[41]

[39]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.

[40]In the structural analysis we do not distinguish between married and non-married couples and assume that all couples can jointly file taxes.

[41]For a detailed description of the German income tax schedule, see Haan & Prowse (2023).

### 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 [42] if no children reside in the individual's household or 0.67 if one or more children reside in the individual's household.

When the 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:

$$\widetilde{\text{SA}}_{i,j,t} = \max\{\text{SAFloor}_{i,j,t} - \widetilde{y}_{i,j,t}, 0\}, \tag{13}$$

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

The social assistance income floor can be written as:

$$\text{SAFloor}_{i,j,t} = G \times E_{i,j,t}. \tag{14}$$

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 euros for each child. 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.[43]

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.[44]

### 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.[45] 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 percent of previous net earnings but does not exceed 1800 euros per month, and there is a floor of 300 euros per month. We approximate the parents' benefit with 67 percent of potential net full-time earnings.[46]

We assume that a household with one or more preschool-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 preschool 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.

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

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

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

[45] 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

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