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Kapitel 3

- In Zusammenarbeit mit Maximilian Blesch, Philipp Eisenhauer, Boryana Ilieva, Peter Haan und Georg Weizsäcker.
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Kapitel 4

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Chapter 2

Causal Misperceptions of the Part-Time Pay Gap

2.1 Introduction

Many developed countries have advanced access to flexible working arrangements since the 1990s, often by easing the transition between full-time and part-time employment through statutory rules (Hegewisch et al., 2009). However, actual take up of part-time employment remains strongly gendered: One in four women in the OECD worked part-time in 2021, but fewer than one in ten men.[1] One reason explaining the gap between availability and take up of part-time work is the negative stigma associated with part-time employment ('flexibility stigma', see Chung, 2020; Williams et al., 2013). Workers associate part-time work with negative career outcomes, including lower chances of promotion (Chung, 2020), as well as short-term (Schrenker, 2022) and long-term wage penalties (Boneva et al., 2021).[2]

In this paper, I study if workers form expectations about the consequences of working part-time based on misguided causal inference. Previous research shows that individuals often struggle to distinguish between correlation and causation.[3] Causal misperceptions can result in behavioral distortions (Spiegler, 2020a), and agents who confuse correlation and causation can be systematically fooled (Horz and Kocak, 2022; Spiegler, 2020b). One particular challenge when inferring from correlational information is the presence of data selection. Individuals may neglect that they only observe a selective sample when they observe the outcomes of other individuals ('selection neglect bias'), which can lead to biased expectations about their own outcomes (e.g. Jehiel, 2018; Koehler and Mercer, 2009; Barron et al., 2019; López-Pérez et al., 2022).

In the context of part-time employment, individuals may try to learn about the consequences of working part-time by observing the career outcomes of other part-time employed workers. However, part-time and full-time workers differ substantially in their

[1] OECD (2022), Part-time employment rate (indicator). doi: 10.1787/f2ad596c-en (Accessed on 15 November 2022)

[2] However, there is also evidence indicating that workers underestimate the long-term effects of part-time employment on their own wage trajectories, in line with overconfidence (Blesch et al., 2021).

[3] For example, individuals expect higher chances of winning the lottery when purchasing lottery tickets in a 'lucky store' that previously sold a winning ticket (Guryan and Kearney, 2008).

characteristics, as well as labor force attachment and work experience (e.g. Blundell et al., 2016; Fernández-Kranz et al., 2015), so observable differences in pay between part-time workers and full-time workers are strongly driven by worker selection and systematic sorting (e.g. Manning and Petrongolo, 2008; Fernández-Kranz and Rodríguez-Planas, 2011). Existing research documents large raw gaps in pay between full-time and part-time workers in the range of 20 to 30 percent (see Schrenker, 2022, for an overview), whereas estimates of selection-corrected part-time wage penalties are usually much smaller (e.g. Manning and Petrongolo, 2008; Schrenker, 2022; Paul, 2016; Aaronson and French, 2004; Hirsch, 2005; Matteazzi et al., 2014; Gallego-Granados, 2019). Hence, workers who infer from observed pay gaps about the consequences of switching between full-time and part-time work may substantially overestimate the true penalty or premium of working different hours, which may lead to suboptimal labor supply choices.

To examine if workers wrongly draw causal conclusions from average full-time/part-time pay gaps, I ask three research questions. First, do workers believe full-time and part-time workers earn different hourly wage rates? Second, what is the perceived causal effect of switching between full-time and part-time employment for a given worker? Third, how do perceived causal effects relate to perceived raw gaps in pay between full-time and part-time workers, and do beliefs reflect selection neglect?

To answer these questions, I implement a survey module combined with an information experiment in the Innovation Sample of the German Socio-Economic Panel (SOEP-IS) between 2016 and 2019. The SOEP-IS is an annual panel survey representative of German households with high quality data collection and face-to-face interviewing. I obtain N=1,362 responses from 369 individuals in the first part of the survey. The experiment is implemented in a separate subsample of the SOEP-IS in Wave 2019, with N=1,425 participants.

In the first part of the survey, I elicit workers' beliefs about the mean hourly wage rate earned by full-time workers in their occupation, as well as the mean hourly wage rate earned by part-time workers in their occupation. I use these measures to quantify respondents' beliefs about the perceived difference in hourly pay between full-time and part-time workers. Furthermore, I measure workers' beliefs about the causal part-time wage penalty. I define the causal part-time penalty as the change in hourly pay that a given worker experiences when switching between full-time and part-time employment. Specifically, I ask respondents to consider a hypothetical scenario of switching between working 40 hours per week and 20 hours per week, *ceteris paribus*, and then provide an estimate of the expected change in hourly wage rates associated with this transition. Respondents provide three different estimates for the hypothetical scenario: i) the predicted wage change for an average full-time worker in their occupation switching to a part-time position; ii) the predicted wage change for an average part-time worker in their occupation switching to full-time; and iii) respondents' self-expected wage change when switching between full- and part-time employment, which depends on the current employment status of the respondent (full- or part-time). The non-experimental survey data allow me to quantify the perceived raw difference in hourly pay between full-time and part-time workers, as well as the perceived causal effect of switching between full- and part-time work. To study selection neglect, I analyze descriptively whether workers distinguish between correlation and causation by examining whether they expect causal effects that are quantitatively similar to the raw wage gap they believe exists between

full-time and part-time workers. To test for selection neglect more formally, I further design and implement an information experiment, described next.

To causally estimate if workers infer from average pay gaps about the causal part-time penalty, I further conduct an information experiment in a separate subsample of the GSOEP. The experiment consists of two treatment groups who receive different information, and one control group that receives no information. Participants are allocated to one of the three groups with equal probability based on random assignment. The first treatment group receives information about the average gap in hourly pay between full-time workers and part-time workers in the German population. I elicit self-beliefs about the causal part-time penalty post treatment, using the same survey instrument as in the non-experimental questionnaire, and exploit the experimentally induced variation in beliefs between the first treatment group and the control group to analyze if individuals draw causal conclusions from correlational information.

I further use the experimental design to study the role of de-biasing and to test whether selection neglect persists when individuals are informed of the data generating process (DGP), as shown in some laboratory settings (Barron et al., 2019) but not others (López-Pérez et al., 2022). To this end, I provide the second treatment group with an alternative information treatment that also reports the average pay gap between full-time and part-time workers, but additionally educates subjects about the selection mechanism driving the observed wage gap. Specifically, the second information treatment points out that observed pay gaps between full-time and part-time workers can largely be explained by differences in work experience.

Finally, I analyze some behavioral implications of worker beliefs about part-time pay. Exploiting the longitudinal dimension of the SOEP-IS, I study descriptively how worker beliefs relate to planned and realized transitions between full-time and part-time employment.

The empirical analyses generate five main findings (described in detail below). First, respondents underestimate the difference in hourly wage rates between full-time and part-time workers in their occupation. Second, workers predict small causal wage penalties for a given worker switching between full- and part-time employment. Third, perceived raw and causal wage gaps are significantly correlated. Fourth, providing correlational information strongly affects beliefs about causal effects. Fifth, de-biasing effectively reduces selection neglect. Taken together, the results provide empirical evidence of causal misperceptions in the context of the part-time wage penalty. Although individuals do not naïvely equate average pay gaps with causal effects, they seem to account only insufficiently for worker selection. In addition, I show that beliefs about part-time pay gaps are predictive of labor supply choices, necessitating the prevention of causal misperceptions to avoid behavioral distortions.

Comparing perceived average wage rates with measures of actual hourly wages in respondents' occupation reveals that workers systematically underestimate differences in hourly pay between full-time and part-time workers.[4] While subjects only moderately overestimate the average wages of full-time workers (by 2.67 percent on average, SD=30.66),

[4]Measures of actual occupational average wage rates are obtained from an additional data set, the *Verdienststrukturerhebung* (VSE, 2018), the only large scale data set in Germany with information on earnings and working hours (see Section 2.3.5 for details).

they strongly overestimate average part-time wage rates, with a mean bias of 9.26 percent (SD = 35.49). As a result, workers underestimate raw wage gaps between full-time workers and part-time workers in their occupation by 6.49 percentage points, or about 50 percent, on average (SD = 14.0). These findings confirm existing empirical evidence on earnings misperceptions in the context of the German labor market, such as persistent biases in beliefs about occupation median monthly salaries documented by Jäger et al. (2022), further adding that individuals are particularly misinformed about the salaries of part-time workers.

When asked to predict the causal effect of switching employment states on their own hourly wages, respondents report moderate expected part-time penalties of 3.4 percent on average. Variation in self-beliefs is substantial (SD = 11.9). Part-time workers expect stronger wage gains from switching to full-time (6.9 percent, SE = 1.3) compared to the wage losses from switching to part-time expected by full-time workers (1.6 percent, SE = 0.9).

I further show that perceived causal wage penalties correlate significantly with perceived raw gaps in pay between full-time and part-time workers. Part-time workers who believe full-time workers in their occupation earn much higher wage rates than part-time workers also expect large wage premiums from switching to full-time employment. Likewise, full-time workers perceiving larger raw wage gaps expect larger part-time penalties, although the association is less pronounced. Coefficient estimates of the elasticity between perceived raw and causal gaps is 0.82 for part-time workers and 0.39 for full-time workers. Hence, part-time workers' expectations about the full-time premium almost mirror perceived raw wage gaps, whereas full-time workers differentiate somewhat more between average pay gaps and causal wage penalties. Notably, the associations remain robust when including, as an additional covariate, different proxies of the occupational part-time wage gap adjusted for worker characteristics, thereby explicitly conditioning on between-occupation differences in the treatment effect of part-time work on wages.

While these findings are suggestive of selection neglect, one might alternatively conjecture that workers who expect stronger causal wage penalties for part-time work have private information about their employer's compensation schemes or their own productivity. A similar concern arises with heterogeneous rewards for full-time work by gender (Hirsch, 2005; Aaronson and French, 2004) or by occupational position (Fernández-Kranz and Rodríguez-Planas, 2011). To address this concern, I use alternative measures of the perceived causal effect based on predicted wage gains and losses for an average worker, allowing me to abstract from the role of private signals. On average, subjects predict a causal part-time wage penalty of 3.3 percent for a typical full-time worker in their occupation (SE = 0.5) and a full-time wage premium of 5.6 percent (SE = 0.7) for an average part-time worker. Relating these alternative estimates with perceived average pay gaps yields very similar results as those obtained from worker self-beliefs, with estimated slopes of 0.36-0.57 for an average full-time worker and 0.71-0.88 for an average part-time worker.

Taken together, the non-experimental analyses provide empirical evidence suggestive of moderate selection neglect bias. Although there is no one-to-one mapping between perceived raw and causal wage gaps, the link is positive and of notable size. A part-time worker who believes that full-time workers earn 30 percent more than part-time workers, on average, also expects a full-time wage premium close to 30 percent. However, it is

important to note that these associations are purely correlational and may be driven by joint unobserved correlates of worker beliefs (also see Bertrand and Mullainathan, 2001).

Estimates based on the information experiment provide additional causal evidence of causal misperceptions. Relative to the control group, individuals who receive correlational information about the average part-time wage gap in the population increase expectations about the causal wage penalty by factor 1.7 (+ 3.49 p.p., $p < 0.01$), with an effect size equivalent to one fourth of the control group standard deviation. I find heterogenous treatment effects by gender and by employment sector, with men and private sector employees reacting more strongly to the correlation treatment. Furthermore, I find that the de-biasing treatment effectively reduces selection neglect. Respondents do not significantly react to the correlational information when they simultaneously receive information about the selection mechanism explaining the influence of work experience on raw wage gaps. Although de-biasing does not fully eliminate the effect of the correlation treatment, providing information about the selection rule substantially reduces and renders insignificant the effect of the correlation treatment (+1.29 p.p., $p > 0.1$). Consistent with work by López-Pérez et al. (2022) showcasing that individuals account for selection effects when they have strong evidence about the DGP, I find that educating individuals about selection effects seems to be effective in mitigating causal misperceptions in the context of the part-time wage penalty.

Finally, I show that beliefs about the part-time penalty are predictive of planned and actual switching between full-time and part-time employment, in line with evidence from Mueller et al. (2021); Boneva et al. (2021), and Wiswall and Zafar (2021), who find that perceptions predict choices. Using data on stated intentions to switch employment states within the next three years, I find that individuals perceiving larger part-time wage gaps also report a lower willingness to switch between full-time and part-time employment. Part-time workers who predict larger full-time wage gains report a 1.77 percentage points higher intention to move to full-time, whereas full-time workers overestimating raw wage differentials report a -0.4 percentage points lower subjective probability to switch to part-time. Similarly, data on realized transitions confirms a positive (albeit weak) link between the perceived returns to part-time work and actual job switching. In sum, worker beliefs and beliefs-biases appear to have behavioral implications, although it must be cautioned that I do not establish a causal link between expectations and actions.

This project contributes to several strands of literatures. Firstly, it adds to existing work on causal misperceptions and selection neglect. In contrast to previous work by Jehiel (2018); Koehler and Mercer (2009); Barron et al. (2019); Spiegler (2020a), and López-Pérez et al. (2022), this paper uses representative survey data to study selection neglect outside laboratory and theoretical settings. Building on the framework developed by Barron et al. (2019), this paper tests several hypotheses from selection neglect theory in a relevant labor market context, the part-time wage penalty. In contrast to Barron et al. (2019), but in line with López-Pérez et al. (2022), I find that individuals who are informed of the underlying selection rule do not exhibit selection neglect bias, thereby affirming a role for de-biasing interventions.

This paper also contributes to a broad literature documenting systematic biases in beliefs about labor market outcomes (e.g. Jäger et al., 2022; Wiswall and Zafar, 2015a; Mueller et al., 2021; Drahs et al., 2018; Schneider, 2020), as well as existing work on earnings

misperceptions. A large literature documents substantial misperceptions with respect to the average earnings of direct colleagues (Cullen and Perez-Truglia, 2022), average occupational salaries (Jäger et al., 2022; Wiswall and Zafar, 2015b), as well as misperceptions about wage gaps by gender (Briel et al., 2021; Settele, 2019), by education (Wiswall and Zafar, 2015a), and by seniority (Cullen and Perez-Truglia, 2022). With respect to part-time employment, empirical evidence remains scarce. Boneva et al. (2021), Schrenker (2022) and Blesch et al. (2021) analyze beliefs about the short- and long-run returns to part-time employment, but none of the existing studies measure misperceptions about the differences in hourly wage rates between full-time and part-time workers. I contribute to this literature by quantifying the beliefs-biases about existing part-time wage differentials, extending previous evidence on salary misperceptions in the context of the German labor market (Jäger et al., 2022).

More generally, this paper also adds to a longstanding literature studying social comparisons (e.g. Cullen and Perez-Truglia, 2022; Card et al., 2012; Fliessbach et al., 2007; Godechot and Senik, 2015; Baumann et al., 2019), as well as sociological work on the 'flexibility stigma' (Chung, 2020; Williams et al., 2013, e.g.). By showing that workers' beliefs about the consequences of working part-time can originate in misguided social comparisons, I highlight that it is important to not only document beliefs, but to better understand whether fears about the career costs of part-time work are warranted and how they can be mitigated.

The remainder of the paper is structured as follows: Section 2.2 provides background information about part-time wage gaps in Germany. Section 2.3 presents the conceptual framework and the empirical design. Section 2.4 contains results from the non-experimental analyses, Section 2.5 presents results from the information experiment. In Section 2.6, I analyze the behavioral implications of worker beliefs and Section 2.7 concludes.

2.2 Background

This section provides empirical estimates of part-time wage gaps and describes the selection of workers into part-time employment in the German context. The Appendix contains additional information about the institutional context.

There exists a sizeable gap in mean hourly pay between full-time workers and part-time workers of 0.22 log points that mostly reflects compositional differences between workers in full-time and part-time employment (Table 2.1).[5]

In comparison to full-time workers, part-time workers have lower educational attainment and lower tenure at the firm, they are more likely to have a temporary contract and hold managerial positions less frequently. Among men, there is a noteworthy positive selection of university educated workers into part-time employment, but part-time workers are also more likely to have no completed degree, with larger differences for men (10.4pp) than for women (3.5pp). The extent to which part-time and full-time workers differ in their characteristics and, hence, hourly pay, varies strongly across occupations (see Table B.7 in the Appendix), with pay gaps being larger in occupations with strong worker and

[5]The empirical estimates in this section are based on VSE and GSOEP data, described in Section 2.3.5.

Table 2.1: Part-Time Wage Gaps and Differences in Worker Characteristics

	Overall			Men			Women		
	FT	PT	Diff.	FT	PT	Diff.	FT	PT	Diff.
Log hourly wage	2.987	2.768	0.219	3.024	2.735	0.290	2.902	2.777	0.126
Highest education (percent)									
No degree	7.3	11.5	−4.1	7.7	18.1	−10.4	6.5	10.0	−3.5
Vocational	62.8	66.3	−3.4	62.4	53.1	9.3	63.7	69.2	−5.5
Upper vocational	5.6	2.8	2.9	6.9	4.4	2.5	2.9	2.4	0.5
Bachelor	4.6	2.9	1.7	3.7	4.0	−0.3	6.5	2.6	3.8
Masters	18.6	15.8	2.8	18.1	18.8	−0.7	19.6	15.2	4.4
PhD	1.1	0.8	0.3	1.1	1.6	−0.4	0.9	0.6	0.3
Tenure (years)	11.6	10.8	0.8	11.7	7.5	4.2	11.4	11.6	−0.2
Managerial position (percent)	6.5	1.8	4.7	7.4	2.9	4.4	4.6	1.5	3.1
Temporary contract (percent)	12.5	17.8	−5.2	11.6	24.1	−12.5	14.7	16.1	−1.4

Notes. VSE 2018. Cells contain weighted sample means for full-time (FT) and part-time (PT) workers and differences in means (Diff). All differences are statistically significant at the 95% level. Sample excludes workers in marginal employment (*Minijobs*).

job segmentation (Figures B.4a - B.4c). A large literature shows that adjusting for occupation, worker and job characteristics substantially reduces the part-time pay gap; most previous studies document only small selectivity-adjusted part-time penalties of about five percent.[6]

2.3 Research Design

This section describes the conceptual framework, the survey instruments, the experimental set-up, and the data. The Appendix contains additional details.

2.3.1 Conceptual Framework

To conceptualize how workers form beliefs about wages when switching between full-time and part-time work, assume worker $i \in \{1, ..., N\}$ currently works either full-time (FT) or part-time (PT), the two states of the world are subsequently denoted by $s \in \{FT, PT\}$. Adopting the potential outcome model (POM) developed by Neyman (1923) and Rubin (1974), there are two potential outcomes for each worker i,

$$Y_{s,i} = \begin{cases} Y_{FT,i} \\ Y_{PT,i} \end{cases}$$

where $Y_{s,i}$ denotes the gross hourly wage worker i would earn in full-time and in part-time employment, respectively. Typically, the Neyman-Rubin-POM is used to describe the missing data problem researchers face when estimating the average causal treatment

[6]For example, see Paul (2016); Schrenker (2022); Gallego-Granados (2019); Stürmer-Heiber and Schneider (2022); Wolf (2002) for estimates of the selectivity-corrected part-time penalty in Germany, Manning and Petrongolo (2008); Connolly and Gregory (2008); Ermisch and Wright (1993) for the UK, Fernández-Kranz et al. (2015); Fernández-Kranz and Rodríguez-Planas (2011) for Spain, and Hirsch (2005); Aaronson and French (2004); Blank (1990) for the US. For an extensive review of the previous theoretical and empirical literature see Schrenker (2022).

effect, $E[Y_{FT,i} - Y_{PT,i}]$, as only one potential outcome is observed for each worker. Here, I propose that the worker faces a similar missing data problem because she also observes only one potential outcome given her state s_i, $Y_{s,i|s_i=s}$,

		Potential outcome	
		$Y_{FT,i}$	$Y_{PT,i}$
State	$s_i = FT$	✓	✗
	$s_i = PT$	✗	✓

and, hence, must form beliefs about the counterfactual outcome, $\tilde{Y}_{s,i|s_i \neq s}$, if she wants to infer the causal effect of switching between the states,

$$\tilde{E}[Y_{FT,i} - Y_{PT,i}|s_i] = \begin{cases} Y_{s,i|s_i=s} - \tilde{Y}_{s,i|s_i \neq s} & if\ s_i = FT \\ \tilde{Y}_{s,i|s_i=s} - Y_{s,i|s_i \neq s} & if\ s_i = PT. \end{cases}$$

Analogous to researchers who utilize group differences in average outcomes of individuals in the different states to solve the missing data problem, worker i may try to infer the effect of switching states on wages from observing the average outcomes of other individuals. Formalizing this idea, and adapting the theoretical framework proposed by Barron et al. (2019), worker i infers the causal effect of switching between full- and part-time work based on observing the following two signals:

1. a private signal, $\rho_i = Y_{s,i|s_i=s} + \eta_i$, and
2. a group signal, $\gamma_i = \bar{Y}_{FT,R_i} - \bar{Y}_{PT,R_i}$,

where $Y_{s,i|s_i=s}$ is the worker's current factual outcome, η_i is an individual-specific unobserved component, and γ_i denotes the difference in average full-time and part-time outcomes, $\bar{Y}_{FT,R_i}$ and $\bar{Y}_{PT,R_i}$, in a reference group the worker may observe, denoted by R_i.

Based on a weighted combination of the two signals, worker beliefs about the causal effect of switching between full-time and part-time employment are described by

$$\tilde{E}[Y_{FT,i} - Y_{PT,i}|s_i] = \ \eta \ + \ \psi \ (\bar{Y}_{FT,R_i} - \bar{Y}_{PT,R_i}) \ + \ \epsilon_i \tag{2.1}$$

where η is the weight on the private signal, ψ is the weight on the group signal, and ϵ_i is an individual-specific randomly distributed error term. Note that for $\eta = 0$, workers anchor beliefs about the counterfactual outcome at their current factual outcome, $Y_{s,i|s_i=s}$. Also note that a positive weight ψ on the group signal does not automatically indicate beliefs-biases. A standard decomposition shows that the group signal reflects a mixture of selection bias and the true treatment effect of part-time work on wages, the causal average treatment effect on the treated (ATT):

$$\bar{Y}_{FT} - \bar{Y}_{PT} = \underbrace{E[Y_{FT,i} - Y_{PT,i}|FT]}_{\text{ATT}} + \underbrace{E[Y_{PT,i}|FT] - E[Y_{PT,i}|PT]}_{\text{Selection Bias (SB)}}$$

Unless the causal ATT in workers' reference group is zero, workers may legitimately view the group signal as a somewhat noisy indicator of the true part-time wage effect. To study if individuals overreact to the group signal and extrapolate from selection bias, it is important to condition on a proxy of the selectivity-corrected part-time wage gap[7]

$$\tilde{E}[Y_{FT,i} - Y_{PT,i}|s_i] = \eta + \psi\,(\bar{Y}_{FT,R_i} - \bar{Y}_{PT,R_i}) + \rho\,(\hat{ATT}_{R_i}) + \epsilon_i \tag{2.2}$$

where $\psi = 1$ benchmarks full selection neglect, that is, a one-to-one mapping of perceived causal and average part-time wage gaps, conditional on true differences in pay between part-time and full-time workers.

Heterogeneous treatment effects Workers may rationally expect part-time wage effects below or above the ATT_{R_i} if treatment effects are heterogeneous within worker reference groups and workers have private information. However, while not at the individual level, on average a discrepancy in beliefs and $ATTs$ indicates beliefs-biases even when treatment effects are heterogeneous. In addition, I utilize various survey instruments to elicit worker beliefs, specifically addressing the issue of heterogeneous treatment effects. To preview, I measure worker beliefs about the causal impact of switching between full-time and part-time work not only on the respondent's own wages, but on the wages of an average worker in their reference group transitioning between part-time and full-time employment, thereby abstracting from private information. I also analyze the asymmetry in beliefs about the wage effect of switching from full- to part-time and from part-time to full-time as an additional dimension of effect heterogeneity.

The next Section 2.3.2 describes the survey instruments to elicit worker beliefs. The Appendix contains an additional classification of workers into different belief types.

2.3.2 Belief Elicitation: Survey Instruments

I measure workers' self-beliefs about counterfactual wage offers $\tilde{Y}_{s,i|s_i \neq s}$ in part-time employment (if the worker currently works full-time) or in full-time employment (if they currently work part-time), using the following survey question:

Q1. *Imagine you switch to a part-time (full-time) job from now on, working 20 (40) hours per week. Please only consider part-time (full-time) jobs that you could carry out with your qualification. Which gross hourly wage do you expect to earn when working part-time (full-time) at 20 (40) hours per week?*

The question fixes counterfactual weekly hours at 20 and 40 hours, respectively, to limit variability in subjective definitions of part-time or full-time work. Individuals report their expected counterfactual wage offer in Euros, based on an open-ended elicitation. To benchmark workers' beliefs about their factual wage, $Y_{s,i|s_i=s}$, I provide survey participants with an estimate of their current hourly wage *prior to eliciting beliefs about the counterfactual situation*, utilizing the responses regarding gross monthly pay and contractually agreed working hours they provided earlier in the survey (see Section B.2.1).

[7] An alternative representation is to net out the ATT from the group signal and only measure the elasticity with respect to the portion of the group signal attributable to selection bias.

The question prompts respondents to consider only comparable jobs in the counterfactual scenario by fixing qualification requirements. Based on individuals' factual wage, $Y_{s,i|s_i=s}$, and their perceived counterfactual wage offer, $\tilde{Y}_{s,i|s_i\neq s}$, I construct workers' self-beliefs about the causal part-time wage effect, $\tilde{E}[Y_{FT,i} - Y_{PT,i}|s_i]$.

I measure workers' beliefs about the average wage level among full-time workers in their reference group, $\tilde{Y}_{FT,R_i}$ with the following question:

Q2. *What do you think is the gross hourly wage of an average full-time worker in your occupation?*

Again, to provide them with a benchmark, workers are reminded of their own current hourly wage prior to receiving the question.

Correspondingly, I elicit beliefs about the average wage level among part-time workers, $\tilde{Y}_{PT,R_i}$:

Q3. *What do you think is the gross hourly wage of an average part-time worker in your occupation?*

The questions on average wage levels explicitly fix the reference group by referring to workers in the respondent's current occupation, thereby allowing me to construct empirical proxies of the true occupational wage levels in full-time and in part-time employment and assess beliefs-biases (Section 2.3.4).[8] Workers in the same occupation also represent a plausible and relevant reference group because respondents may consider switching employers when thinking of transitioning between full-time and part-time employment, whereas it is less likely (albeit possible) that they anticipate moving to an entirely new occupation.

Finally, to address the concern of private information in the presence of heterogeneous treatment effects, I measure beliefs about the causal part-time wage effect, $\tilde{E}[Y_{FT,i} - Y_{PT,i}|s_i]$, in an alternative way. Specifically, I elicit beliefs about the counterfactual wage offer when switching between part-time and full-time work, $\tilde{Y}_{s,i|s_i\neq s}$, not only for the respondent herself, but also for an average worker in their reference group, utilizing the following two questions:

Q4. *Now imagine that an average full-time worker in your occupation, who currently earns [X] Euros per hour, moves to a part-time position. Which gross hourly wage do you expect for this worker in part-time?*

Q5. *Now imagine that an average part-time worker in your occupation, who currently earns [Y] Euros per hour, moves to a full-time position. Which gross hourly wage do you expect for this worker in full-time?*

Note that X and Y are individual-specific responses to questions Q2 and Q3, respectively, and are subsequently used as measures of the factual wages, $Y_{s,i|s_i=s}$, when constructing $\tilde{E}[Y_{FT,i} - Y_{PT,i}|s_i]$. While private information - such as knowledge of firm-specific reward schemes - may generate rational deviations from average treatment effects in respondents' self-beliefs (Q1), private signals should not impact rational beliefs about the average causal effect in the occupation (Q2-Q5). In addition, these questions allow me to study

[8] Alternatively, the question could have prompted workers to think of employees within the same firm, in this case, assessing beliefs-biases would require matched employer-employee data.

if individuals predict asymmetric wage responses between shifting from full-time to part-time and from part-time to full-time. By cross-randomizing the order of questions Q4 and Q5, I can also analyze consistency bias in response behavior.

In addition to these core questions, I implement an information experiment, described next. A full description of the survey modules used for additional sensitivity analyses is presented in the Appendix.

2.3.3 Information Experiment

To study if workers draw causal conclusions from correlational data, I implement an information experiment in the beliefs survey. In the experiment, I provide a random subset of respondents with information about the raw average wage gap between full-time workers and part-time workers. I then elicit workers' self-beliefs about counterfactual wage offers, using the same survey instrument as presented previously, and utilize the experimentally induced variation to analyze if workers pay attention to correlational information when forming beliefs about the causal part-time wage penalty.

The experimental design allows me to (i) remove existing information barriers that arise in real markets due to pay intransparency; (ii) avoid the identification challenges posed by omitted variable bias when interpreting the relationship between average pay gaps and worker beliefs (also see Bertrand and Mullainathan (2001)); and (iii) test if educating respondents about the role of selection effects mitigates selection neglect (de-biasing).

Experimental Set-up and Hypotheses

The survey experiment involves two alternative information treatments that are assigned to two distinct treatment groups. An additional control group receives no information treatment. Respondents are allocated to one of the three groups with equal probability based on random assignment. All participants first receive an estimate of their current hourly wage to benchmark their beliefs (see Section 2.3.2 and Section B.2.1). The control group then directly reports self-beliefs about counterfactual wage offers, based on the survey instrument Q1 presented in Section 2.3.2. The two treatment groups also report self-beliefs, but only after receiving one of the two information treatments described below.

The first treatment provides purely correlational information about the average wage differential between full- and part-time workers in Germany:

Treatment T1. (Correlation treatment)
"Research shows that average part-time working employees in Germany earn about 20 percent less per hour than average full-time working employees earn per hour."

The second treatment also provides information about the raw correlation, but additionally contains an explanatory sentence educating respondents about the data-generating process (DGP), i.e. the role of selection effects in driving the correlation:

Treatment T2. (Correlation treatment + De-biasing)
"Research shows that average part-time working employees in Germany earn about 20 percent less per hour than average full-time working employees earn per hour. However, this wage differential can mostly be explained by the fact that full-time working employees have more work experience on average."

Hypotheses I use the experimentally induced variation in beliefs between individuals receiving the pure correlation treatment (T1) and individuals belonging to the control group to test if individuals adjust beliefs towards the provided correlational benchmark, as hypothesized by selection neglect theory (Barron et al., 2019). Likewise, I use random variation in beliefs between the control group and individuals receiving the combined correlation/de-biasing treatment (T2) to test for selection neglect when individuals are informed about the underlying data generating process (DGP). Correspondingly, I exploit the variation in beliefs between the two treatment groups T1 and T2 to study the effectiveness of de-biasing.

2.3.4 Empirical Benchmarks

To measure biases in beliefs, I construct the empirical equivalents of $\gamma_i = \bar{Y}_{FT,R_i} - \bar{Y}_{PT,R_i}$, the average part-time wage gap in the worker's occupation, and of the ATT_{R_i}, the true wage effect of switching between full-and part-time work conditional on occupation. Arguing that worker beliefs should match these empirical benchmarks rests on certain assumptions, which I spell out below. I follow Jäger et al. (2022), who point out that specifying objective benchmarks for worker beliefs is 'notoriously challenging', in utilizing and comparing several available proxies, described below and in the Appendix.

Raw occupational wage gaps I proxy γ_i by measuring the raw part-time wage gap as the log difference in gross hourly wages between full-time workers and part-time workers in worker i's occupation. Occupation is defined based on 3-digit KldB codes using the German Classification of Occupations 2010 (*Klassifikation der Berufe, KldB*) which is tailored to capture particular features of the German labor market (see Section B.4.1 for details and examples). I use the German *Verdienststrukturerhebung* (VSE) for precise estimates of γ_i by occupation, denoting the empirical estimates by $\hat{\gamma}_i$ (see Section 2.3.5 for more information about the VSE data).

Corrected occupational wage gaps To proxy the true ATT_{R_i} in worker i's occupation, I decompose $\hat{\gamma}_i$ into two parts, using standard Blinder-Oaxaca decomposition: (i) a portion that is explained by selection effects, such as differences in the characteristics of workers selecting into full-time and part-time jobs; and (ii) a portion that is unexplained by differences in worker characteristics, capturing differences in the returns between full-time and part-time work. I run this decomposition separately for each 3-digit occupation cell, again using VSE data, and utilize the resulting empirical estimates of the residualized wage gap to proxy the ATT_{R_i} at the occupational level.[9] There are two major caveats with this approach. First, there might be heterogeneous effects of part-time work

[9]In the decomposition, I residualize the raw wage differential between full-time and part-time workers based on compositional differences in education, age, tenure, gender, region (east/west), contract type (permanent/temporary), managerial responsibility, firm size, sector (public/private), minimum wage branch, female share and union coverage.

on wages even within occupation groups. For instance, effects might differ by gender or by worker age, thereby compromising the suitability of these estimates as a benchmark for worker self-beliefs about the causal effect, as discussed previously. Second, the decomposition relies on selection on observables, which can generate biased estimates of the ATT_{R_i} if workers select into part-time and full-time employment based on unobservable characteristics. The VSE data lack the panel dimension required for more elaborate modeling of the selection mechanism. I discuss alternative measures of the ATT_{R_i} based on different data in the Appendix.[10] However, given that I compute the ATT_{R_i} for a particular occupation conditional on having selected into this occupation, much of the unobserved selection into part-time employment is implicitly accounted for due to strong occupational segregation between part-time and full-time workers, such as the selection of workers favoring part-time employment into part-time compatible occupations (also see Adda et al. (2017)).

2.3.5 Data and Samples

I measure beliefs about part-time wage effects for a representative sample of German workers by integrating the questions described in Section 2.3.2 and the information experiment into the Innovation Sample of the German Socio-Economic Panel (GSOEP).[11] I further use the *Verdienststrukturerhebung* (VSE) collected by the Federal Statistical Office to construct the empirical benchmarks described in Section 2.3.4.[12]

Data

GSOEP Innovation Sample (SOEP-IS) The SOEP-IS is a broad annual panel study representative of private households in Germany. Survey design and field work mirror that of the core GSOEP: participating households are initially selected based on multistage random sampling with regional clustering and interviews are conducted face-to-face using computer-assisted personal interviewing (CAPI). Beyond featuring similar survey administration, the SOEP-IS also shares a sizeable part of the questionnaire with the core GSOEP and achieves similarly high response rates averaging at 84 percent (Zweck and Glemser, 2020). In addition, the SOEP-IS accommodates further innovative modules that are designed by the research community and must pass a competitive review process. I design and implement the questions presented in Section 2.3.2, as well as the information experiment, in different SOEP-IS modules between 2016-2019. Excluding the experiment, I collect responses of 1,362 observations from 369 individuals. The survey experiment is implemented in Wave 2019 of the SOEP-IS, using a different subsample of the SOEP-IS to rule out overlap with related questions from previous waves. For both treatment groups, interviewers read out the content of the information treatment to the respondents in face-to-face interviews. The experiment contains 1,425 observations (462 control, 457

[10] In the Appendix, I discuss two alternative approaches of measuring corrected part-time penalties, utilizing the wage changes following observed switches between full-time and part-time employment in longitudinal data, as well as the linear wage mandate in public sector occupations. The results presented in this paper are robust to alternative measures of the corrected part-time wage gap.

[11] I gratefully acknowledge access to the GSOEP data (SOEP, 2018) and the GSOEP Innovation Sample data (SOEP-IS, 2020) provided by the Research Data Center of the Socio-Economic Panel (FDZ SOEP).

[12] I gratefully acknowledge access to the VSE data (VSE, 2018) provided by the Research Data Center of the Federal Statistical Office and Statistical Offices of the Federal States.

treatment I, 506 treatment II). Item non-response on the main beliefs questions is between 6 and 22 percent. Sample conditions are described in Section 2.3.5.

Verdienststrukturerhebung (VSE, 2018) The VSE is a survey of German firms collected in 4-year intervals by the German Federal Statistical Office and contains payroll record information of 1.01 million employees from 71,000 firms. Firms are selected using stratified sampling by federal state. For public sector employers, the information is directly gathered from the *Personalstandsstatistik*, a database covering the universe of employees in the public sector. For private sector firms, participation in the survey is mandatory, resulting in high representativeness. Firms submit responses through an electronic transmission system. The reporting basis for the 2018 wave is the month of April. The VSE contains exact information on employees' gross earnings and working hours obtained from payroll records that I use to construct precise measures of part-time wage gaps. In addition, the VSE contains a large set of employee characteristics, including education, age, gender, tenure and occupational position, as well as linked establishment characteristics such as union coverage, branch and sector. I utilize this information to adjust average wage differentials between full-and part-time workers for worker selection into part-time employment and job segmentation, again by occupation, using decomposition analysis (see Section 2.3.4).

Worker beliefs from the SOEP-IS and occupational part-time wage gaps from the VSE are matched based on *KldB* occupation codes (match rate based on 3-digit *KldB* for the SOEP-IS sample is 98.2 percent).

Sample and Descriptive Statistics

The sample consists of workers in full-time or part-time employment. I further restrict the sample to exclude workers in marginal employment (*Minijobs*), in self-employment, in military or community service, or in training. Pensioners and individuals above age 65 are dropped. I deflate all monetary variables, including worker beliefs, to 2018 values using the consumer price index and trim them at the bottom and the top two percent of the distribution. In the experimental analysis, I further drop individuals with missing or invalid responses in weekly hours or in actual or expected wages. After these restrictions, the experimental estimation sample consists of 900 individuals (286 control, 275 treatment T1, 339 treatment T2). Table B.1 in the Appendix reports descriptive statistics for the main sample and the experimental sample. Table B.2 presents the raw and restricted sample sizes for the experimental sample and Table B.3 shows summary statistics separately by randomization status.

2.4 Beliefs about Part-Time Pay Gaps

This Section documents workers' beliefs about full-time and part-time wage rates and shows how the perceived returns to full-time work covary with beliefs about average wage gaps. Section 2.5 presents estimates based on the information experiment. The Appendix contains additional results.

Summary of results *Workers strongly underestimate the difference in hourly wage rates between full-time workers and part-time workers in their occupation, with a mean bias of 6.5 percentage points. When asked to predict the causal wage change induced*

by a switch between full-time and part-time employment, individuals expect a part-time wage penalty of 3.4 percent for themselves, of 3.3 percent for an average full-time worker switching to part-time, and of 5.6 percent for an average part-time worker switching to full-time. Expectations about the part-time penalty correlate significantly and positively with perceived average gaps in pay between full-time and part-time workers (Slope = 0.4-0.9), consistent with moderate selection neglect bias.

2.4.1 Beliefs about Average Full-Time and Part-Time Wage Rates

Here I compare respondents' estimates of the average full-time and part-time wage rate in their occupation to actual wage rates. Actual wage rates are measured based on the VSE data and 3-digit occupation codes obtained from the German Classification of Occupations (KldB 2010). Perceived wage rates are elicited in the SOEP-IS, after respondents receive an estimate of their own current hourly wage, which serves as a benchmark and which is calculated based on their previous responses regarding monthly earnings and weekly hours worked (see Section 2.3.2).

Table 2.2: Misperceptions of Average Part-Time and Full-Time Wage Rates in Workers' Occupation

	Bias (beliefs-actual)		Absolute error	
	Mean	S.D.	Mean	S.D.
Bias avg. full-time wage (in %)	2.67	30.66	23.78	19.48
(S.E.)	(1.97)		(1.25)	
Bias avg. part-time wage (in %)	9.26	35.49	26.68	25.11
(S.E.)	(2.30)		(1.63)	
Bias avg. FT-PT wage gap (in p.p.)	−6.49	14.00	12.16	9.48
(S.E.)	(0.91)		(0.62)	

Notes. SOEP-IS 2019 (I5), N=324. Cells show mean biases and mean absolute errors in beliefs about the average wage level of full-time workers and part-time workers in respondents' occupations. Biases defined as the log-deviation from actual occupation mean wages obtained from the VSE 2018, with occupation based on 3-digit KldB 2010. S.E. = standard error, S.D. = standard deviation.

Conditional on being told what their own current hourly wage is, workers give approximately correct estimates of the average full-time wage rate in their occupation (Table 2.2, Figure B.7a). The mean deviation is only 2.7 percent and statistically insignificant. In contrast, respondents systematically overestimate average hourly wage rates of part-time workers in their occupation, with a mean bias of 9.3 percent (Table 2.2, Figure B.7b). Hence, individuals implicitly underestimate the difference in hourly pay between full-time workers and part-time workers in their occupation by about 50 percent, or 6.5 percentage points on average.

2.4.2 Perceived Causal Part-Time Wage Penalties

Next, I analyze workers' predictions of the causal wage change associated with a switch between full-time and part-time employment. I use three different instruments: (i) self-beliefs about the effect of switching between full -and part-time work on the respondent's

own wages; (ii) predicted wage losses for an average full-time worker in the respondent's occupation switching to part-time; and (iii) predicted wage gains for an average part-time worker switching to full-time.

Table 2.3: Worker Beliefs about the Causal Part-Time Wage Penalty

	All workers		FT workers		PT workers	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Self-beliefs PT penalty	3.42	11.94	1.61	11.76	6.86	11.60
(S.E.)	(0.80)		(0.97)		(1.32)	
Predicted loss FT worker	3.31	8.24	2.71	7.18	4.48	9.95
(S.E.)	(0.54)		(0.57)		(1.11)	
Predicted gain PT worker	5.59	10.44	5.70	10.74	5.36	9.89
(S.E.)	(0.69)		(0.87)		(1.11)	

Notes. SOEP-IS 2019 (I5), N=324. Cells contain perceived causal part-time wage penalties for a switch between working full-time (FT) and part-time (PT) in percent. S.E. = standard error, S.D. = standard deviation.

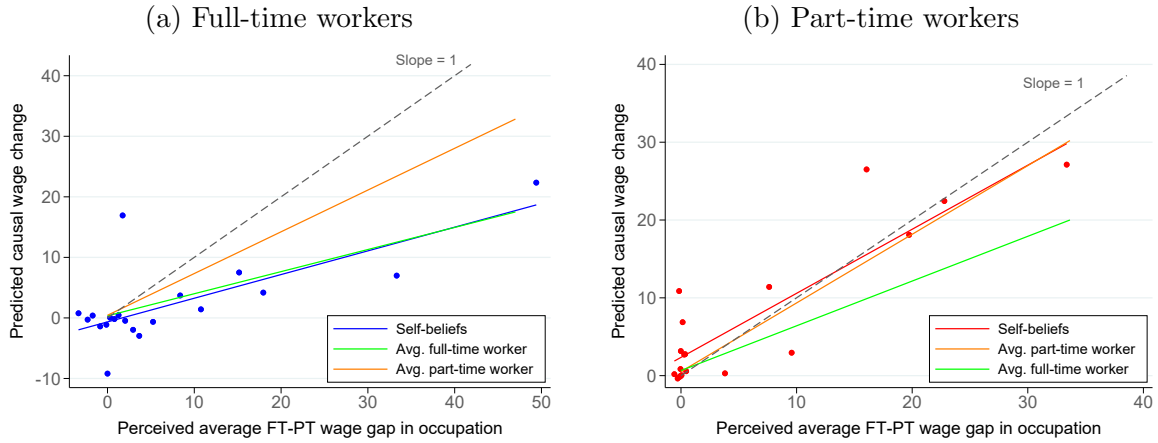
I document similar findings for all three outcomes (Table 2.3). Workers, on average, expect a part-time penalty of 3.4 percent on their own wages, a part-time wage loss of 3.3 percent for an average full-time worker, and a 5.6 percent full-time premium for an average part-time worker (Table 2.3). The asymmetry between predicted wage losses and gains for full- and part-time workers mirrors the asymmetry in self-beliefs by respondents' employment status: full-time workers expect smaller losses from switching to part-time on their own wages (1.6%) compared to the full-time wage premia expected by part-time workers (6.9%).

Variation in beliefs about the causal part-time penalty is substantial, with a standard deviation of 11.9 percent for self-beliefs. Notably, standard socio-demographic characteristics and job attributes barely explain the observed variation in perceived part-time penalties (Table B.8 in the Appendix). However, there is considerable disagreement about the size of the part-time penalty across occupational areas (Table B.8).

2.4.3 Selection Neglect and Causal Misperceptions: Descriptive Evidence

In Figure 2.1, I show how expectations about the part-time penalty relate to perceived average gaps in pay between full-time and part-time workers. The binned scatter plots with the solid fitted lines indicate the empirical relationship in the data. The dashed lines indicate the hypothetical scenario in which respondents expect a part-time penalty that is identical to the perceived difference in average wage rates. Hence, a slope of one benchmarks the full selection neglect scenario with a one-to-one mapping between perceived causal and raw wage gaps (also see Section 2.3.1). To account for between occupation differences in the true return to full-time work, the graphical analyses condition on occupation-specific estimates of the corrected part-time penalty.[13]

[13]In the main specification, I use estimates obtained from Oaxaca-Blinder decompositions, additionally I provide a set of sensitivity checks based on alternative estimates of the corrected part-time penalty from wage changes following switches between full- and part-time work, as well as linear wages in the



Notes: Binned scatter with linear fit of the predicted causal part-time penalty plotted against the perceived raw wage gap between full-time and part-time workers, residualized for corrected occupation part-time wage gaps, separately for full-time workers (panel a, N=143) and part-time workers (panel b, N=76). Dashed 45-degree line benchmarks full selection neglect. Occupation based on 3-digit KldB 2010. Data sources: SOEP-IS 2019 (beliefs), VSE 2018 (raw and corrected gaps).

Figure 2.1: Perceived Causal and Raw Part-Time Wage Gaps

I find a positive and significant association between predicted causal penalties and perceived average pay gaps, consistent with moderate selection neglect. Estimates of the slope based on workers' self-beliefs are 0.39 (S.E. = 0.085) for full-time workers (Figure 2.1, Panel a) and 0.82 (S.E. = 0.11) for part-time workers (Figure 2.1, Panel b). Hence, part-time workers' expectations about the full-time premium almost mirror perceived raw wage gaps. Full-time workers differentiate notably more between average pay gaps and causal wage penalties. Using alternative definitions of the causal part-time penalty based on average full-time and part-time workers yields similar results. Workers predict full-time wage gains for an average part-time worker that are almost identical to the raw pay gap (Slopes=0.71-0.88). Predicted part-time wage losses for an average full-time worker are correlated less with perceived raw pay gaps (Slopes=0.36-0.57).

While purely descriptive, the empirical findings presented in this section suggest that workers account only insufficiently for selection effects. Although there is no one-to-one mapping between predicted causal effects and perceived correlations, the link is positive and of notable size. A part-time worker who believes that full-time workers earn 30 percent more than part-time workers, on average, also expects a full-time wage premium close to 30 percent. The results from this descriptive exercise suggest that workers may draw causal conclusions from observed pay gaps, neglecting the influence of worker selection. The Appendix presents additional material on the perceived selection of workers into part-time (Section B.5.2). The next section studies causal misperceptions based on the survey experiment.

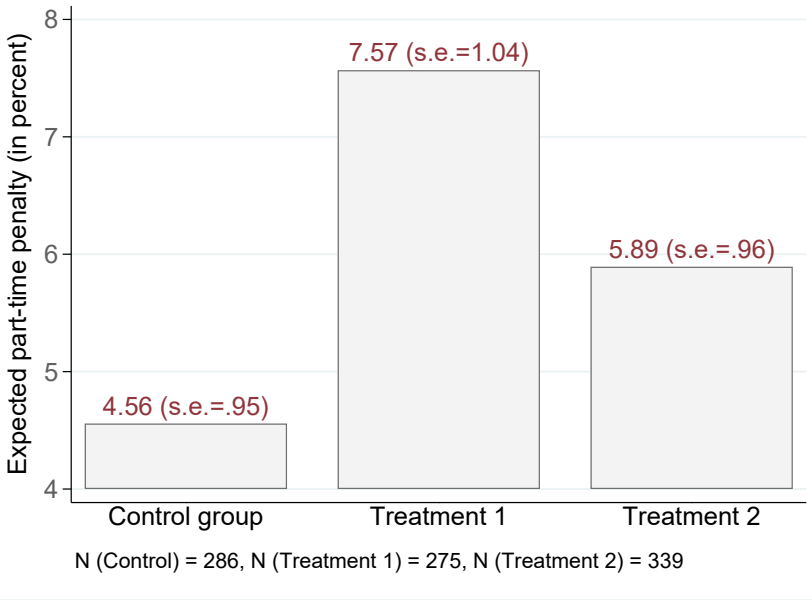
public sector (additional information is presented in the Appendix).

2.5 Survey Experiment: Irrational Attention to Correlation?

Summary of experimental findings *When receiving correlational information about the raw wage gap between full-time and part-time workers, respondents expect significantly larger part-time pay cuts (+ 3.49 p.p., $p < 0.01$). The effect size is equivalent to 1/4th of the baseline (control group) standard deviation, or to an increase by factor 1.7. De-biasing reduces selection neglect and renders the treatment effect insignificant (+1.29 p.p., $p > 0.1$).*

2.5.1 Experimental Results

In Figure 2.2, I show raw sample means of the expected part-time wage penalty post treatment. Individuals in the control group expect a part-time penalty of 4.56 percent on average (SE=0.95), individuals in Treatment group 1 expect a penalty of 7.57 percent (SE=1.04), and individuals in treatment group 2 expect a part-time penalty of 5.89 percent on average (SE=0.96).



Notes: Post-treatment sample means, with robust standard errors (s.e.) in parentheses, of the self-expected part-time wage penalty. Treatment group 1 received the pure correlation treatment, treatment group 2 received the correlation and de-biasing treatment. Data source: SOEP-IS 2019.

Figure 2.2: Experimental Results

Estimates of information treatment effects are presented in Table 2.4. Panel A contains bivariate estimates and Panel B shows treatment effects adjusted for key observables. I use the multivariate estimates from Panel B as the preferred specification because of moderate imbalances in some observable characteristics in the estimation sample (see Table B.3).

The experimental evidence supports the notion that individuals pay strong attention to correlational information. Individuals in Treatment group 1 expect significantly larger

causal part-time wage penalties than individuals in the control group who receive no information about raw average gaps (Table 2.4, Column 1). The difference in expected pay cuts amounts to 3.49 percentage points (p<0.01) and is roughly equivalent to 1/4th of the control group standard deviation (SD=15.89). The variation between T1 and the control group corresponds to an increase in expectations by factor 1.7.

Table 2.4: Experimental Results: Information Treatment Effects

	Correlation treatment (T1 vs. C)	Correlation inc. de-bias (T2 vs. C)	Overall treatment (Treat vs. C)	De-biasing effect (T2 vs. T1)
Panel A				
Treatment effect (bivariate)	3.37**	1.64	2.41**	−1.73
	(1.41)	(1.35)	(1.18)	(1.42)
Constant	4.27***	4.27***	4.27***	7.64***
	(0.95)	(0.95)	(0.95)	(1.04)
Panel B				
Treatment effect (adjusted)	3.49***	1.29	2.34**	−2.25*
	(1.34)	(1.29)	(1.13)	(1.35)
Constant	3.61	6.38*	2.95	6.16*
	(3.36)	(3.28)	(2.65)	(3.34)
Observations	556	620	894	612

Notes. SOEP-IS 2019. Dependent variable is the expected part-time penalty in percent. Panel A shows bivariate treatment effects, Panel B shows multivariate results adjusted for employment status (part-time/full-time), gender, education (basic/middle/university), age, region (east/west), employment sector (private/public), an indicator for firm size (>/< 200 employees) and a constant. Treat=T1+T2. Six individuals with missing values in the control variables were dropped. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

However, on a positive note, individuals also react strongly to the de-biasing treatment. Individuals in Treatment group 2 expect moderately larger part-time penalties than those in the control group, but the difference is small (1.29pp, 1/12th of baseline SD) and not statistically significant (p>0.1). Hence, respondents do not significantly react to the correlational information when they simultaneously receive information about the selection mechanism explaining the raw wage gap between full-time and part-time workers (Table 2.4, Column 2). Although de-biasing does not fully eliminate the effect of the correlation treatment, providing information about the influence of work experience on observed pay gaps substantially reduces and renders insignificant the effect of the correlation treatment (Table 2.4, Column 4). Hence, educating individuals about selection effects seems to be effective in mitigating selection neglect bias in this context.

In the next section, I study heterogeneous responses to the information treatments and further analyze for which groups de-biasing is most effective.

2.5.2 Heterogeneous Treatment Effects

I present treatment effect estimates stratified for different subgroups in Table 2.5 and report significance tests from interacted models in Table B.15 in the Appendix. Sample stratification substantially reduces the sample sizes. While none of the presented group differences are statistically significant at conventional levels, the subgroup analysis points to some interesting variation in the responsiveness to the different treatments. For example, male workers react more strongly to the pure correlation treatment (+4.10pp,

p< 0.05) than women (3.22pp, p>0.1), suggesting male workers are more likely to infer about the causal part-time wage penalty based on correlational information. There are several possible explanations for this finding. Barron et al. (2019) show that self-experimentation reduces selection neglect. Women are more likely to switch between full- and part-time work during their career and may rely less on learning from others than men who lack self-experimentation in part-time employment. Job segmentation between full- and part-time sectors further reduces men's opportunities to learn about hours-based wage differentials from personal contacts, making them more susceptible to the information provided in the treatment. However, estimation results also indicate that men react more to the de-biasing treatment than women (-3.11pp, p<0.1 vs. -1.31pp, p>0.1). Similarly, full-time workers respond more to de-biasing than part-time workers (-2.71pp, p<0.1 vs. -0.72, p>0.1).

Table 2.5: Experimental Results: Subgroup Analysis

	Correlation treatment (T1 vs. C)	Correlation inc. de-bias (T2 vs. C)	Overall treatment (Treat vs. C)	De-biasing effect (T2 vs. T1)
Full sample	3.49***	1.29	2.34**	−2.25*
Women	3.22	2.24	2.74	−1.31
Men	4.10**	0.76	2.32	−3.11*
Full-time	3.52**	0.76	2.12*	−2.71*
Part-time	3.79	3.53	3.80	−0.72
University	4.95*	0.93	2.88	−3.45
No university	3.25**	1.44	2.24*	−1.91
Age > 45	3.03	1.54	2.25	−1.96
Age < 45	3.35*	0.62	1.91	−2.82
Eastern Germany	1.70	−2.05	0.03	−4.11
Western Germany	3.60**	1.70	2.66**	−1.89
Public sector	0.03	1.82	1.27	1.63
Private sector	4.30***	0.80	2.48*	−3.40**
Firm size > 200	3.76**	1.62	2.61*	−2.06
Firm size < 200	3.88*	1.30	2.43	−2.59
Temporary contract	3.74	3.99	3.24	−3.99
Permanent contract	3.36**	0.94	2.12*	−2.50*
Managerial position	3.51	0.53	1.96	−2.94
No managerial position	4.00**	2.19	3.05**	−1.73

Notes. SOEP-IS 2019. Dependent variable is the expected part-time penalty in percent. Cells contain coefficient estimates by subgroups of bivariate treatment indicators from multivariate regressions with controls for employment status (part-time/full-time), gender, education (basic/middle/university), age, region (east/west), employment sector (private/public), an indicator for firm size (>/< 200 employees) and a constant. Treat=T1+T2. Six individuals with missing values in the control variables were dropped. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The most striking difference in treatment responsiveness arises with respect to employment sectors. Private sector employees react strongly to the correlation treatment (+4.30, p< 0.01), whereas public sector employees barely respond (+0.03, p>0.1). Moreover, private sector employees respond strongly to de-biasing (-3.4, p<0.05), whereas the de-biasing treatment has an opposing effect on public sector employees who expect slightly

larger part-time penalties after receiving Treatment 2 compared to Treatment 1 (+1.63, p>0.1). These results are of interest for at least two reasons. First, they suggest that strong and transparent wage regulation can mitigate selection neglect in wage expectations. Individuals in public sector occupations with linear wage setting are less likely to misinterpret the correlational link between earnings and part-time status and, hence, do not infer from average part-time pay gaps about the impact of working part-time on their own wages. Second, the findings reveal heterogeneous effects of de-biasing. When receiving information about the importance of work experience in generating wage differentials between full-time and part-time workers, public sector employees diverge from the linear-wage assumption and update their beliefs toward the provided correlational benchmark. One possible explanation is that the de-biasing treatment prompts public sector employees to consider second-order effects of working part-time, such as not being promoted to higher hierarchical positions that are associated with higher salary ratings. The de-biasing treatment in this information experiment is rather simplistic, so these results may not fully transfer to more complex real-life applications. Nevertheless, the results illustrate the importance of tailoring information campaigns to specific target groups to avoid adverse effects.

2.6 Behavioral Implications

In the final section, I exploit the longitudinal dimension of the SOEP-IS and use follow-up data from the latest panel wave to study how worker beliefs about part-time pay relate to planned and realized transitions between full-time and part-time employment.

2.6.1 Planned Employment Transitions

In waves 2017-2019 of the GSOEP, respondents in sample I5 report the subjective probability to switch employment status in the near future based on the following survey question which differs for full-time and part-time workers:

Q7. *Now we would like to know how likely you think it is that you will switch from full-time to part-time (from part-time to full-time) in the next 3 years.*

Respondents report the subjective probability in percent using a given interval between 0 and 100. Among full-time workers, 26 percent indicate a positive probability to switch to part-time in the next three years. Among part-time workers, 43 percent report a positive probability to switch to full-time. The full distribution of responses is presented in Figure B.10 in the Appendix.

I analyze the association between planned transition rates and worker beliefs about part-time pay using OLS in Table 2.6. Worker self-beliefs are collected in all waves, but only wave 2019 contains worker beliefs about wage losses or gains of switching for an average worker in their occupation and beliefs about average pay gaps. Regressions are run separately by employment status and condition on worker characteristics as well as on actual raw and adjusted occupational part-time pay gaps.

Overall, individuals who predict larger part-time wage gaps also report a lower willingness to switch between full-time and part-time employment. For part-time workers, there is a positive and significant association between predicted full-time wage premia for an average

Table 2.6: Worker Beliefs and Planned Employment Transitions

Dep.Var. = Planned transition (in %)	FT workers		PT workers	
	(1)	(2)	(3)	(4)
Self-beliefs PT penalty	−0.048	−0.149	−0.144	−0.216
	(0.061)	(0.111)	(0.129)	(0.574)
Predicted loss FT worker		−0.193		0.096
		(0.432)		(0.758)
Predicted gain PT worker		0.546		1.666**
		(0.388)		(0.716)
Perceived raw gap		−0.389*		−0.168
		(0.220)		(0.656)
N	464	114	214	66
Sample	2017-19	2019	2017-19	2019

Notes. SOEP-IS 2017-2019. Dependent variable is the self-reported subjective probability to switch from full-time to part-time employment (FT workers) or from part-time to full-time employment (PT workers) within the next three years, in percent. Coefficient estimates from OLS regressions with controls for true average raw and adjusted occupation part-time wage gaps, gender, education, age, region (East/West), public sector employment and firm size. Standard errors clustered at the person level in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

part-time worker and their own intention to switch to full-time (+1.7pp, p<0.05). For full-time workers, the link between planned transitions and predicted wage losses for average full-time workers is negative, as one would expect, although statistically insignificant. Moreover, full-time workers who overestimate the raw pay gap between full-time and part-time workers in their occupation report a lower willingness to switch to part-time in the next three years (-0.4, p<0.1).[14] Taken together, these results indicate that planned employment choices relate to perceived losses and gains of working different hours. Next, I explore the association between beliefs and actual employment choices.

2.6.2 Realized Transitions between Full- and Part-Time Work

Annual transition rates between full-time and part-time employment in the GSOEP average at below five percent, generating only limited variation in employment status during the survey period. Nonetheless I can show that worker beliefs about the part-time wage penalty are predictive of actual transition rates (Table 2.7).[15]

Part-time workers expecting stronger full-time wage premiums are significantly more likely to switch from part-time to full-time within a year. Similarly, full-time workers who expect larger part-time wage penalties are less likely to switch from full-time to part-time employment. Moreover, I show that stated intentions about job switching are predictive of actual job switching, corroborating the relevance of the first stage results presented

[14]One can interpret the coefficient on the perceived raw pay gap as an indication of workers overestimating the raw gap because the regressions condition on actual measures of the occupational raw pay gap.

[15]Table B.16 in the Appendix contains the full set of estimation results including covariates.

Table 2.7: Worker Beliefs and Realized Employment Transitions

Dep.Var. = Transition in t+1 (yes/no)	FT workers		PT workers	
	(1)	(2)	(3)	(4)
Self-beliefs PT penalty	−0.001	−0.021	0.003**	0.035*
	(0.001)	(0.024)	(0.001)	(0.019)
Planned transition probability	0.001	0.013	0.004***	0.032***
	(0.001)	(0.010)	(0.001)	(0.009)
N	351	351	152	152
Estimation	LPM	Logistic	LPM	Logistic

Notes. SOEP-IS 2017-2019. Dependent variable is a binary indicator of transitioning from full-time to part-time (full-time workers) or from part-time to full-time (part-time workers) in the next year. Coefficient estimates from linear probability models (LPM) and logistic regressions with controls for true average raw and adjusted occupation part-time wage gaps, gender, education, age, region (East/West), public sector employment and firm size. Standard errors clustered at the person level in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

above. In sum, the findings from this descriptive exercise suggest that worker beliefs and beliefs-biases regarding part-time pay may have relevant behavioral implications, although it must be cautioned that I do not establish a causal link between expectations and actions.

2.7 Discussion

Correlation can be a natural starting point to infer causation whenever the causal link between actions and outcomes is not observed directly: College graduates live longer. Women with children earn lower salaries. There are numerous examples from everyday life where true causal linkages are obscured, whereas correlation is salient. However, learning from correlational data is challenging and individuals can make mistakes. This paper provides novel empirical evidence of causal misperceptions in the context of the part-time wage penalty. Guided by selection neglect theory and based on representative survey data from Germany, I quantify and assess workers' beliefs about the consequences of working part-time on wages. I show that workers underestimate raw differences in pay between full-time and part-time workers. Further, I document a significant correlation between perceived raw pay gaps and the expected causal effect of working part-time. An additional information experiment confirms a causal link between perceived raw and causal part-time wage gaps. Moreover, subjective beliefs about the full-time/part-time pay differential are predictive of planned and actual transitions between full-time and part-time employment, necessitating the prevention of causal misperceptions.

Economists trained in the art of causal analysis may sneer at the temptation to infer causality based on correlational data. Yet, given our everyday struggles to adjust correlations for confounding variables, self-selection, or reverse causality - should we not be surprised, if not offended, if individuals in their everyday lives were equally capable of identifying causal effects? So far, empirical evidence on selection neglect bias remains scarce. This paper attempts to advance our understanding of how individuals form beliefs about causal mechanisms in a relevant labor market application. Future studies may

investigate the prevalence and the implications of causal misperceptions across different contexts.

Chapter 3

Biased Wage Expectations and Female Labor Supply

3.1 Introduction

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

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

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

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

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

The structural model allows us to also assess the consequences of belief biases. Simulations of the model show that the bias translates into an increased propensity of part-time employment by about eight percentage points on average across the population of Germany's female employees. This result is produced by counterfactually imposing rational expectations in the model, and comparing its predictions to those that generate from the full model with biased beliefs. Interestingly, lower expected returns to part-time work experience would induce about half of the responding women to increase working hours to full-time and the other half to leave employment, thereby increasing both full-time employment and non-employment by about the same amount. However, there is noteworthy response heterogeneity. In particular, we find that employment effects are strongest for women with college education: Over the full life-cycle, de-biasing would reduce part-time employment of college-educated women by about 13 percentage points, while full-time employment would increase by about eight percentage points. Correspondingly, we find the strongest welfare effects of de-biasing for college educated women, whose lifetime income would increase by about three percent, on average.

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

To derive these results, we include tailored questions into the Innovation Sample of the

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

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

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 and Manski, 2007; Hurd et al., 2011; Drerup et al., 2017; Breunig et al., 2021b), housing markets (Armona et al., 2019; Kuchler and Zafar, 2019), and human capital formation and labor markets (Arcidiacono et al., 2020; Boneva et al., 2021; Delavande and Zafar, 2019; Jäger et al., 2022; Wiswall and Zafar, 2021). We add to it our emphasis on biased long-run wage expectations that we examine as a possible driver for human capital accumulation. Previous studies have analyzed the effects of part-time work perceptions on current wages (Schrenker, 2022; Stevens et al., 2004) but not their effects on long-run outcomes.[4]

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

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

[4]For detailed surveys of the fast-growing literature on expectations data, see Kosar and O'Dea (2022)

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

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

The remainder of this paper is organized as follows. Section 3.2 describes the data environment and sample. Section 3.3 presents our novel evidence on wage expectations and estimates the returns to experience as they are perceived by the respondents. In Section 3.4, we estimate the realized returns to experience, juxtaposing it with its perceived analogues. Section 3.5 presents the structural model, Section 3.6 reports and discusses the results of its estimation, and Section 3.7 presents the policy simulations. Section 3.8 concludes.

and Mueller and Spinnewijn (2022) as well as other surveys that appeared in the same collection. An overview of long-run economic expectations of German households, including some of the data used in this paper, is given in Breunig et al. (2021).

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

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

3.2 Data

This Section presents the data samples. We use two large sub-samples from the German Socio-Economic Panel, described in Section 3.2.1.[7] Section 3.2.2 outlines the main sample restrictions, while additional sample restrictions that are required for the estimation of the structural model appear in Appendix C.1.2. Appendix C.1.1 contains a detailed definition of all relevant variables.

3.2.1 The German Socio-Economic Panel (SOEP)

The SOEP consists of two separate but related annual surveys, the SOEP core sample and the Innovation Sample SOEP-IS. Both the SOEP core sample and the SOEP-IS are longitudinal surveys that are carefully designed to be representative of German households (Goebel et al., 2019). The SOEP-IS was established in 2011 and supplements the SOEP core sample by enabling the inclusion of new research questions. Recruitment method, survey design and administration are almost identical. Appendix Table C.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 3.3, into the SOEP-IS in order to measure the perceived returns to full-time and part-time work. The SOEP core sample is far larger than the SOEP-IS, allowing us to estimate the corresponding realized returns to experience. Also, the SOEP core sample has a long panel dimension that we exploit to estimate the realized returns in connection with part-time and full-time labor supply choices. Specifically, the core SOEP contains detailed labor market trajectories including information about wages, employment, household formation and further demographic characteristics over time. These year-respondent level variables can also be integrated into our structural model of labor supply over the life cycle.

3.2.2 Sample Restrictions

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

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

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

are, however, always excluded.[9]

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

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

Section 3.3.1 introduces the survey instruments used to measure the respondents' beliefs and Section 3.3.2 summarizes the responses descriptively. Section 3.3.3 presents the empirical strategy for estimating the perceived returns to experience, with the corresponding estimates appearing in Section 3.3.4.

3.3.1 Survey Instruments

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

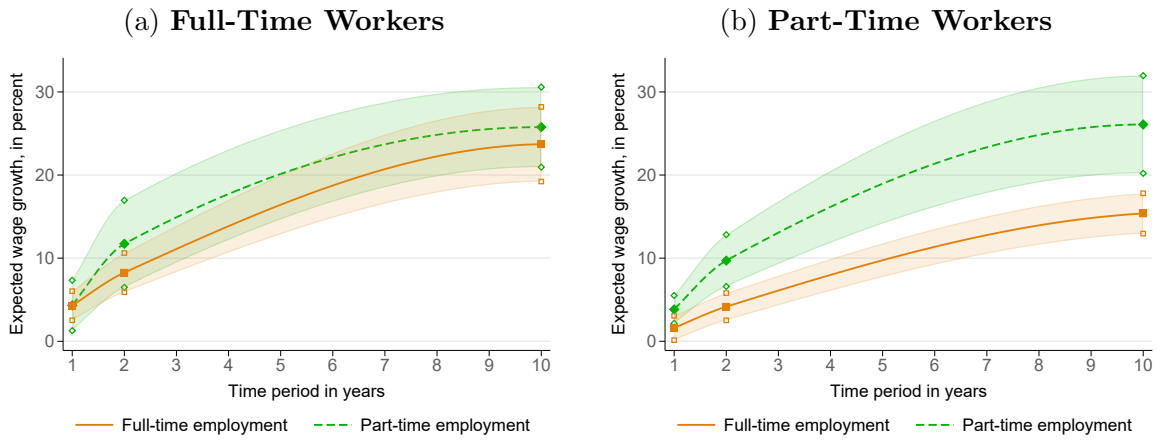
In more detail, respondents report their perceived returns to experience in three steps. In the first step, they report their expected earnings in one year, in two years and in ten years, holding constant their current state of self-reported employment (full-time or part-time). In the second step, full-time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

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

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

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

Evidence of expected wage growth profiles is presented in Figure 3.1, separately for full-time and part-time working female employees. Table 3.1 shows sample averages of expected wage growth across all women and for additional subgroups.



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

Figure 3.1: Expected Wage Growth in Full-Time and in Part-Time Employment

Expected wage increases denote changes in percent relative to wages in the year of the survey response. The depicted expectation averages show a clear pattern: respondents expect no part-time penalty in earnings growth, in that the expected hourly wage from working part-time remains close to that of full-time. Differentiating between the two plots in the figure, we see that full-time working women expect wage growth to be the almost exactly the same in full- and part-time employment. Part-time workers even expect a stronger part-time wage growth. This pattern is surprising at first glance, but it is consistent with many possible selections of self-justifications of the part-time choice (Bertrand and Mullainathan, 2001). Overall, women expect similar earnings growth in part-time and in full-time employment in the short run, and expect higher wages in part-time relative to full-time employment in the medium and long run, i.e. after two and ten years. On average, reported 1-year-out expectations show perceived earnings increases by three percent in part-time employment and four percent in full-time employment (Table 3.1, first versus second column); after two years, respondents expect wages to increase by six percent in full-time work and 11 percent in part-time work; after ten years, the average increase in expected earnings is 19 percent in full-time work and 25 percent in part-time work.

Across the different subgroups that we consider, no-one expects a part-time penalty in earnings growth. However, relevant differences appear by level of education, age and

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

Table 3.1: Expected Wage Growth in Part-Time and Full-Time Employment (in %)

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

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

3.3.3 Estimation of the Perceived Returns to Experience

We use the elicited expectations to describe the expected wage process. Specifically, we estimate the perceived returns to experience in part-time and in full-time employment as expected by the survey respondents, according to Equation (3.1):

$$log(Ew_{it}) = \alpha + \zeta log(E_{it}^{Full}) + \beta log(E_{it}^{Part}) + \mu_i + \epsilon_{itp} \tag{3.1}$$

where Ew_{it} denotes the expected gross hourly wage that individual i expects to earn at time t.[10] The experience variables, one for part-time employment, E_{it}^{Part} and one for full-time employment, E_{it}^{Full}, are specified according to the horizon of the expectation questions, taking the values zero (for today's earnings), one year, two years and ten years, $t \in \{0, 1, 2, 10\}$. In addition, we include an individual-specific fixed effect in our main specification, denoted by μ_i.[11] We use a log specification of the experience terms to capture potential non-linear effects of experience. In a set of sensitivity checks, we show that the main findings are robust to various functional forms including a linear experience specification (see Section 3.3.4).

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

Table 3.2 presents the estimated experience coefficients, in different specifications with and without individual-specific fixed effects. The estimations in Column 1 and 2 only use the information of expected future wages, whereas the estimations in Column 3 and 4 also include information about observed and counterfactual wages in the current period (t=0). In addition, the Table provides test statistics indicating whether the experience terms in part-time and full-time employment are significantly different.

In line with the descriptive evidence, the regression results show that individuals expect similar returns to experience both in part-time employment and in full-time employment. Depending on the specification and the sample, we find an expected wage elasticity with respect to full-time experience of 0.065-0.085. Considering the specification in Column 1, the wage elasticity amounts to 0.08, i.e. an increase in full-time experience by ten percent increases expected wages by about 0.8 percent. For part-time experience, the expected wage elasticity varies between 0.08-0.09. Importantly, in all specifications, the difference in the returns to experience in part-time work and full-time work is small; in specifications where it is significantly different from zero, the effect is higher for the returns to part-time work.[12]

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

[11] In an alternative specification, we estimate Equation (3.1) by OLS. In this specification, we omit the individual fixed effects, but alternatively add a vector of individual-specific covariates that are constant over t but may vary across respondents i. Covariates include an indicator for current employment status, age, education, tenure, years of unemployment, region, migrational background, firm size, public sector employment, marital status and number of children.

[12] In contrast to Boneva et al. (2021) who show that individuals predict earnings losses for part-time

Table 3.2: Expected Annual Returns to Full-Time and Part-Time Experience

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

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

We also consider the results for different subgroups by education (Columns 2-4 in Table 3.3). The results show the same pattern as for the full sample (Column 1). For none of the education groups we find a statistically significant difference in the expected returns to part-time and full-time experience; i.e., no subgroup expects a penalty in part-time experience. In Table C.4, we extend the heterogeneity analysis and repeatedly confirm the same pattern for different subgroups.

Table 3.3: Expected Annual Returns to Full-Time and Part-Time Experience by Education

	Total	Low education	Medium education	High education
	(1)	(2)	(3)	(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 C.2.4, we provide evidence that our main result is robust to various changes in the specification. We show that the results of the specification

working mothers, we document that women expect similar earnings growth in part-time and full-time employment when asked about their own wage trajectories. One potential explanation would be that women are generally aware of part-time career penalties, but, in line with overconfidence, underestimate the dynamic effect of part-time work when asked about their own earnings paths.

with linear experience effects are very similar. The returns of an additional year of part-time and full-time experience vary between 1.4-1.9 percent and the difference between the two experience effects is not significant at the five percent confidence level. Moreover, the findings do not change when adjusting wage expectations for price increases and focusing on real instead of nominal wages. Finally, we show that the results are similar when eliciting beliefs in terms of hourly wages instead of monthly earnings.

3.4 Realized Returns to Experience

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

3.4.1 Female Employment and Wages

The first two panels of Figure 3.2 show the importance of part-time work for female employment, documenting the shift from non-employment to part-time employment since the 1990s. Non-employment rates of women have been strongly decreasing over the last 30 years. At the same time, we see a steady increase in part-time employment, explaining most of the increase in overall employment. The full-time employment rates slightly fluctuate over time, but, overall, the share of full-time working women did not change very much between 1990 and 2018. The level and increase in part-time employment over time does not strongly differ by education: In Panel (b), we show that the part-time shares for women with low, medium and high education increase at similar rates.

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

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

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

endogeneity of experience, individual effects and differences between the groups.

3.4.2 Returns to Experience: Reduced Form Evidence

To estimate the realized returns to education, we specify a wage equation similar to Equation 3.1, in which the actual years of experience in part-time and in full-time work differentially affect hourly wages:

$$log\omega_{it} = \alpha + \zeta logE_{it}^{Full} + \beta logE_{it}^{Part} + X_{it}\gamma + \mu_i + \epsilon_{it}, \tag{3.2}$$

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

Formally, we augment Equation 3.2 and introduce control functions to account for selection into employment (λ^e), selection into full-time work (λ^h), and endogeneity of experience in part-time employment (λ^f) and in full-time employment (λ^p).

$$log\omega_{it} = \alpha + \zeta logE_{it}^{Full} + \beta logE_{it}^{Part} + X_{it}\gamma + \mu_i + \lambda^e + \lambda^h + \lambda^f + \lambda^p + \epsilon_{it}, \tag{3.3}$$

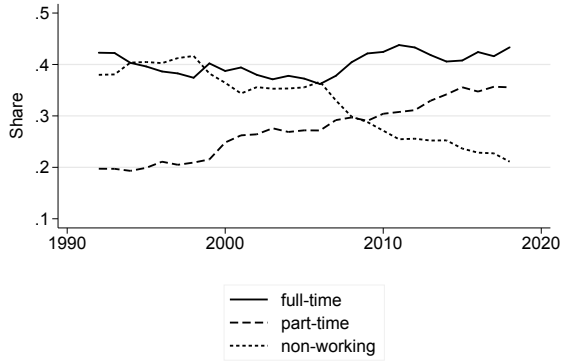
We estimate the wage equations separately for women with low, medium and high education.

In Table 3.4, we present estimates of the wage equation using fixed effects regressions with and without control functions. The specifications of the control functions and the estimation results are relegated to Appendix C.3.

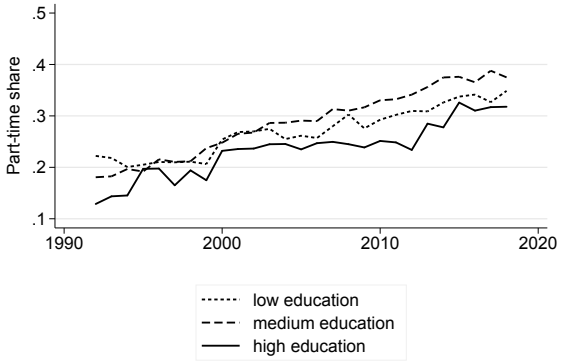
We find similar patterns in all specifications and for all education groups: The realized returns to full-time experience are always considerably larger than the realized returns to part-time experience. Depending on the specification, the experience effect (elasticity) for full-time work lies between 0.09-0.1 for low educated women, i.e. an increase in the years of experience of ten percent increases wages by 0.9-1 percent. For medium educated

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

(a) **Employment Shares**

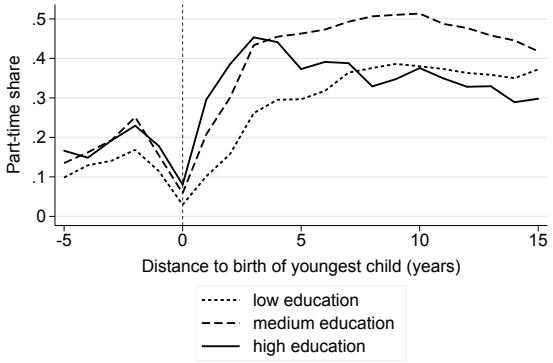


(b) **Part-Time Employment by Education**

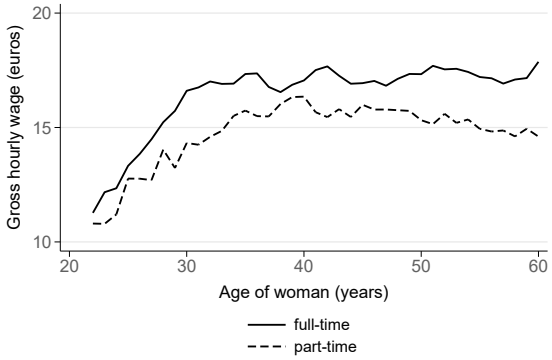


(c) **Part-Time Work across the Life-Cycle**

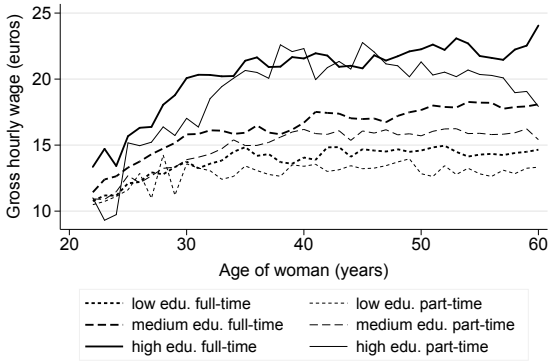
(d) **Fertility and Part-Time Employment**



(e) **Wage Trajectories**



(f) **Wage Trajectories by Education**



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

Figure 3.2: Employment and Wages of German Women 1992-2018

Table 3.4: Estimated Returns to Full-Time and Part-Time Experience

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

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

women, the elasticity is slightly higher (0.17-0.18), and for highly educated women it is between 0.2-0.22. In contrast, the estimated returns to part-time work experience are smaller than 0.06 for all education groups and in all specifications. F-tests on the equality of the returns to experience in full-time and part-time employment are rejected in all specifications. Thus, we can clearly document a penalty to part-time experience in the realized wage trajectories. For low educated women, the difference is smaller but still statistically significant. This is consistent with the finding that returns to full-time experience are lower for low educated individuals and therefore more similar to the returns to part-time experience, see e.g. Blundell et al. (2016). In Appendix C.3, we show that our results are robust to changes to the functional form of the wage specification: Returns to full-time experience are also significantly higher than returns to part-time experience when including an indicator for part-time work in the current period and in a specification with linear and quadratic experience effects.

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

Comparing estimates of the realized returns with women's expectations (Table 3.2), we observe a strong beliefs-bias in the perceived returns to experience. While realized and expected returns to full-time work experience are comparable in size, expectations about the returns to part-time experience strongly diverge from realized returns to part-time work. This result is the motivation and the basis for the subsequent structural analysis, in which we further explore and quantify the implications of biased expectations. Specifically, we build a structural model to quantify the implications of biased beliefs for employment behavior and life time earnings. In addition, we use the model to evaluate the implications of various policy reforms when individuals have biased beliefs.

3.5 Structural Analysis

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

3.5.1 Overview of the Model

The structural model is similar to the life-cycle models of female labor supply developed in e.g. Blundell et al. (2016) or Adda et al. (2017). One key novelty in contrast to the previous literature is that we do not impose rational expectations about human capital accumulation in the wage processes. Instead, we explicitly allow for potentially biased beliefs about the returns to experience, with the standard assumption of rational

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

expectations being nested within this framework. The life-cycle model includes the following main features: i) a choice of female labor supply which includes non-employment, part-time and full-time employment, ii) a wage process with differential human capital accumulation in part-time and full-time employment, iii) a description of the relevant elements of the tax and transfer system including child care costs, and iv) exogenous processes of household formation and male life-time earnings. We estimate all processes separately by education (low, medium and high education) and model choices of women from the moment they complete education and enter the labor market. As experience accumulation in the late working career has only minor effects on wages, we define the last period $\bar{t}$ as age 50. Therefore, we can abstract from early retirement rules and disability programs which become relevant after that age.

Time is discrete, and a period corresponds to a year. As in Blundell et al. (2016), we model household formation, fertility, and the earnings process of the male partner outside the structural model. Female employment and consumption decisions depend on these processes and the counterfactual policies account for the heterogeneity in these dimensions.[16] In the following, we describe the central elements of the structural model in more detail. The exogenous processes are presented in Appendix C.4.

3.5.2 Utility and Value Function

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

$$u(c_t, h_t; \theta, Z_t) = \frac{(c_t/n_t)^\mu}{\mu} exp\{U(h_t, \theta, Z_t)\} \tag{3.4}$$

with

$$U(h_t, \theta, Z_t) = \begin{cases} 0, & \text{if } h_t = N, \\ \theta_{(h_t)} + Z_t'\beta(h_t), & \text{if } h_t = P \text{ or } F, \end{cases} \tag{3.5}$$

where $\beta(h_t) = \beta_F + \beta_P \cdot \mathbf{1}\ (h_t = P)$. The vector Z summarises other characteristics that we consider relevant determinants of the preferences for work. In particular, we control for the presence of children and the age of the youngest child. The parameter vector β_F corresponds to the preference for full-time work associated with the presence of children, generally, and the additional effect when a child is aged 0-2, 3-5, and 6-10. The parameter β_P corresponds to the change in the experienced disutility of work when the woman works part-time instead of full-time. In the above flow utility (3.4), c_t/n_t represents consumption per adult equivalent, while μ governs risk aversion and intertemporal substitution. We set μ to -0.56. The vector $\theta = (\theta_p, \theta_f)$ contains the persistent unobserved heterogeneity in part-time and full-time employment in the form of discrete mass points. Each woman is one of k numbers of types, such that the individual type is

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

associated with a specific preference for full-time work θ_F, and a specific level of preference for part-time work θ_P.

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

$$V_t(X_t) = \max_{\{c_\tau, h_\tau\}_{\tau=t,\dots,\bar{t}}} E\{\sum_{\tau=t}^{\tau=\bar{t}} \delta^\tau u(c_t, h_t; \theta, Z_t)|X_t\}, \tag{3.6}$$

We assume exponential discounting and set the discount factor δ to 0.98. Agents who are low and medium educated enter the model when aged 22, while highly educated agents enter the model aged 24 (for more details, see Appendix C.4.1).

Households maximize the value function to the following budget constraint

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

Consumption is determined by labor earnings, the tax and transfer system (T), child benefits (CB) and child care costs (CC). Labor earnings of the household consist of the woman's own labor earnings, $h_t w_t$, and the exogenous labor income of the partner, $\tilde{w}_t$, if present in the household. Contributions to and from the tax and transfer system depend on household earnings and the structure of the household, and child benefits and child care costs are determined by the number and the age of the children, and vary between part-time and full-time employment. For the estimation of the structural model, we focus on the period 2007-2018. During that time period, the general structure of the tax and transfer system was only slightly changed.[17] In Appendix C.5, we provide a detailed description about the rules of the tax and transfer system and how the rules are implemented in the structural model.

3.5.3 Wages

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

$$ln\, w_{st} = \gamma_{s,0} + \gamma_{s,F}\, ln(e_F + 1) + \gamma_{s,P}\, ln(e_P + 1) + \xi_{st} \tag{3.7}$$

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

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

3.5.4 Subjective Expectations

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

$$\bar{\gamma}_{s,P} = \alpha_s \cdot \gamma_{s,P} \tag{3.8}$$

where α governs the bias in beliefs. The standard assumption of rational expectations is nested in this framework for $\alpha = 1$. We calculate α from the ratio of the elicited beliefs about the returns to experience, ζ_s and β_s (see Table 3.2) and the estimated reduced-form parameters for the realized contribution of part- and full-time years of experience $\gamma_{s,F}$ and $\gamma_{s,P}$ (see Table 3.4),

$$\alpha_s = (\beta_s/\zeta_s)/(\gamma_{s,P}/\gamma_{s,F}) \tag{3.9}$$

It is important to note that in this specification, individuals do not update beliefs. This assumption can be justified in two ways. First, previous findings suggest that the part-time penalty is as good as absent in the short-run (Manning and Petrongolo, 2008). It only emerges after longer part-time employment spells. Given the dynamics, it is plausible that both the existence as well as the magnitude of the penalty are hard to gauge in a real-life setting. The penalty can only be observed by an individual who chooses to work part-time for multiple years in a row and compares herself to a similar coworker who has spent the time working full-time on the same job. Second, the expectations data presented in Table 3.1 suggest that older individuals overestimate wage growth in part-time employment in the same way as young individuals with less labor market experience. This provides further evidence that learning does not seem to take place as individuals progress through their working careers.

3.5.5 Estimation and Identification

Estimation proceeds in two stages. In the first stage, we use the SOEP sample to estimate the exogenous processes of the model; the rate of marriage and divorce, the employment and earnings process of the male spouse, and births over the life-cycle. We further use the estimated reduced-form parameters of the returns to part-time and full-time experience and set the scale of the wage shock to a level such that it fits the variance of wages. The specifications for the different processes and estimation results are presented in Appendices C.4.2 and C.4.3.

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

ω denote the collection of parameters to be estimated in the second stage. The indirect inference estimator of ω is given by:

$$\widehat{\omega} = \underset{\omega}{\operatorname{argmin}} \left(\widehat{\psi} - \widehat{\psi}(\omega)\right)' \Sigma \left(\widehat{\psi} - \widehat{\psi}(\omega)\right), \tag{3.10}$$

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

Table 3.5: Moments

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

3.6 Results

3.6.1 Parameter Estimates

First, we evaluate the effects of the differential returns to full-time and part-time experience obtained from the reduced-form analyses over the life-cycle, using the structural model. Figure 3.3 shows how for different levels of education, hourly wages in part-time employment evolve over time relative to hourly wages in full-time employment. When entering the labor market, hourly wages in full-time and part-time employment do not differ. However, we see a strong decline in the relative wage trajectory for women with medium and high education. For women with low education, wages in full-time employment and part-time employment evolve quite similarly. The estimated experience profiles are very similar to the findings in previous studies (Blundell et al., 2016), who show considerably lower part-time penalties for women with high school and secondary education, respectively.

Relating the estimated part-time penalties to women's subjective expectations, we quantify the discrepancy between the expected and realized returns to experience. Specifically, we calculate the bias parameters α according to Equation 3.9 for each education group. The estimated bias is about two for women with low education. This suggests that these women expect a return to part-time experience relative to full-time experience which is twice as large as the relative realized return. The bias significantly increases for women with medium and high education and is estimated to be about five. Why do we find

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

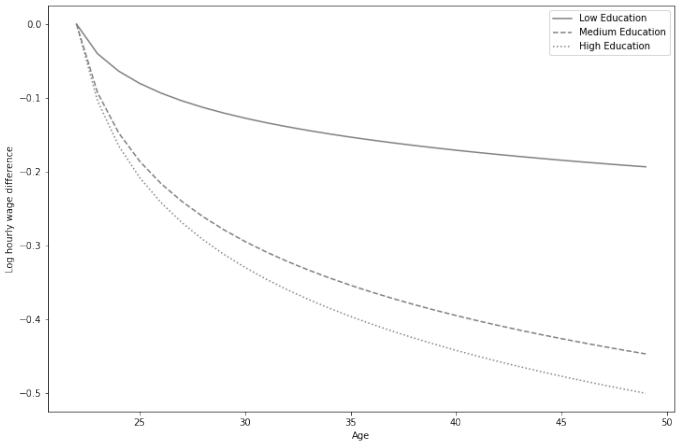


Figure 3.3: Part-Time Penalty

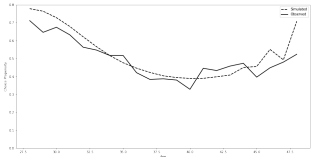
this sizable education gradient in the bias? As we have documented above, irrespective of the educational level, women do not expect a part-time experience penalty. However, the realized part-time experience level is particularly pronounced for medium and college-educated women.

In Table 3.6, we turn to the structural parameters related to individual preferences. As mentioned above, we set the coefficient μ to -0.56, which translates to a risk aversion of 1.56 that is consistent with previous studies, see, e.g. Blundell et al. (2016). When interpreting the coefficients, it is important to note that positive and larger values of the preference parameters imply higher disutilities. Moreover, as defined in Equation 3.5, the coefficients of part-time work are additive to the coefficients of full-time work. For all groups, the coefficients of full-time employment have a positive effect and show that women experience disutility in full-time employment. As expected, disutility is stronger for women with children and specifically high when the age of the youngest child is between zero and two. The strong preference for part-time relative to full-time work is consistent with biased expectations about the returns of part-time experience. In our model, we capture that women over-estimate the returns to part-time experience. This suggests that women should place a higher value on part-time employment than in a standard model with rational expectations, and that the effect should be strongest for women with high education, who have the largest bias.

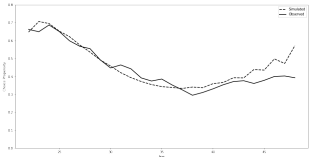
3.6.2 In-Sample Fit

The estimated life-cycle profiles of employment are very similar to the observed counterparts. In Figure 3.4, we show the age profiles of the three employment states for the different education groups. For all education groups, the model captures the decline in full-time employment during the ages when women have young children, as well as the increase at higher ages. The model further replicates the shares in part-time employment which are increasing with age, and the shares in non-employment which are markedly higher for women with low education.

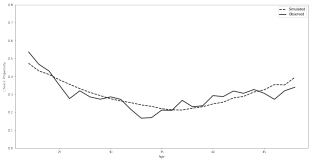
(a) **Full-Time, High Education**



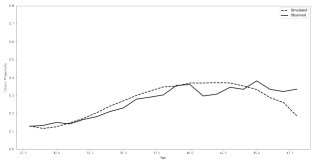
(b) **Full-Time, Medium Education**



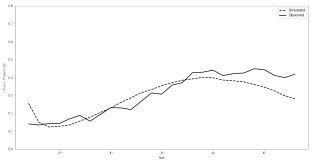
(c) **Full-Time, Low Education**



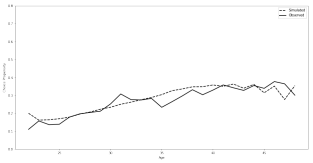
(d) **Part-Time, High Education**



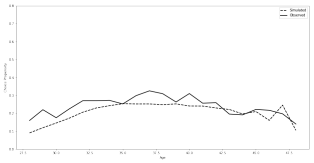
(e) **Part-Time, Medium Education**



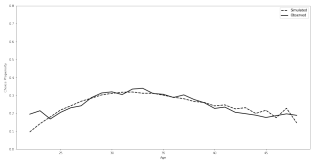
(f) **Part-Time, Low Education**



(g) **Unemployed, High Education**



(h) **Unemployed, Medium Education**



(i) **Unemployed, Low Education**

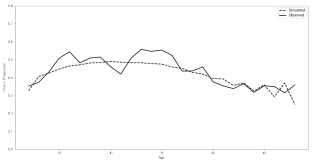


Figure 3.4: Life-Cycle Employment Profiles

Table 3.6: Preference Parameters

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

3.7 Simulations

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

3.7.1 Implications of Biased Beliefs

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

The overall effects for all women and by education over the life-cycle are summarized in Table 3.7. The effects strongly vary by education. Since women with low education have only a modest bias, we only find moderate changes in employment when women expect the true wage process. Over the full life-cycle, part-time employment among low educated women decreases by about five percentage points. Interestingly, both full-time employment and non-employment increase by about the same amount. This suggests that the lower expected returns to part-time experience in the de-biased scenario induces about half of the low-educated women to leave employment and the other half to increase working hours to full-time employment. The mixed employment effects explain why the

Table 3.7: Life-Cycle Effects of Rational Beliefs

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

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

effects on life-time earnings are close to zero among the low educated. For women with medium and high education, the effects are very different. For these groups, de-biasing has stronger employment effects. In the scenario in which the expected and realized returns to experience are consistent, the share of part-time employment is drastically lower (by 7.8 percentage points for women with medium education and by 13 percentage points for women with high education). The simulations further reveal that labor supply responses among the medium educated are dominated by substitution from part- to non-employment, whereas college-educated women are more likely to move from part-time employment into full-time employment. Correspondingly, we find the strongest life-cycle effects of de-biasing for college educated women, whose lifetime income would increase by about three percent, on average.

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

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

3.7.2 Policy Reforms

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

3.7.3 Individual Taxation

As described in Appendix C.5, according to the rules in Germany, couple households are taxed jointly with full income splitting. This system imposes a higher marginal tax rate

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

Our simulations show that in line with the incentives, this policy reform would increase employment and earnings. As this reform has a direct effect on the current income, it has strong implications for part-time and full-time employment even in the presence of biased beliefs about the returns to experience (Table 3.8). We find that, on average, non-employment is reduced by about three percentage points over the working life. The size of the effect is similar across the different educational groups. At the same time, part-time and full-time employment increases. The effect for part-time employment (1.98 p.p.) is even larger than for full-time employment (1.05 p.p.). The larger effect for part-time employment has two sources. First, there is a direct incentive effect of individual taxation to change from non-employment to part-time employment. Second, given women's biased beliefs, the long-run costs of part-time employment are not incorporated, rendering this choice more attractive.

Table 3.8: Life-Cycle Effects of Individual Taxation

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

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

3.7.4 Child Care Costs

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

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

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

Table 3.9: Life-Cycle Effects of Reduced Child Care Costs

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

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

3.8 Conclusion

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

Chapter 4

Working Longer: Causal Effects on Career Trajectories of Raising the Statutory Retirement Age

4.1 Introduction

Delaying retirement entry is a common policy response to the increased financial pressures on social security systems imposed by demographic change. Pension reforms that raise the retirement age predominantly aim at increasing the labor force participation of older workers (OECD, 2021).[1] However, extending the working life can also lead to behavioral adjustments among younger individuals, who may change career decisions in anticipation of a longer working horizon, potentially shifting entire career and wage growth profiles over the life-cycle.

An emerging literature has started to explore the forward-looking effects of pension reforms on the labor market outcomes of individuals who are still relatively far from retirement. For example, Carta and De Philippis (2022) document positive effects of raising the full retirement age on participation rates among middle-aged women in Italy, with significant spill-overs into spousal labor supply. Gohl (2022) confirms forward-looking employment effects of pension reforms for Germany, showing that labor supply responses are concentrated among individuals in low-physical intensity and service sector occupations. Further, Gohl (2022) and Hairault et al. (2010) find increases in job search intensity among unemployed individuals with a longer expected working horizon, while de Grip et al. (2020), Brunello and Comi (2015), and Gohl et al. (2021) document increased participation in on-the-job training for workers facing delayed retirement entry. Yet overall, empirical evidence on the effects of extending the working horizon on the labor market trajectories of younger individuals remains relatively scarce.

We contribute to this active area of research by analyzing the effects of prolonging the working horizon on occupational mobility and wage dynamics among middle-aged workers in Germany. Typically, earnings growth occurs predominantly in the beginning of

[1] A large literature confirms positive labor supply effects for workers close to retirement, for example Mastrobuoni (2009); Behaghel and Blau (2012); Staubli and Zweimüller (2013); Atalay and Barrett (2015); Manoli and Weber (2016); Engels et al. (2017); Geyer et al. (2020); Geyer and Welteke (2021).

the working life (Rubinstein and Weiss, 2006), as workers ascend the career ladder and achieve wage gains by promotion to higher professional positions (Bayer and Kuhn, 2019). By the age of 45, wage growth frequently levels off, and rarely rises towards the end of the working life. However, an increase in the expected duration of the work horizon has the potential to change typical career and wage growth trajectories by incentivizing professional advancement during later stages of the working career. One theoretical argument in line with this is given by human capital theory, which predicts higher investments into human capital with an increase in the pay-out period over which returns to investment can be reaped (Gohl et al., 2021; Becker, 1962; Ben-Porath, 1967). Consequently, individuals expecting to work longer may seek further training in the middle of their career to achieve wage gains through career advancement (Gohl et al., 2021; de Grip et al., 2020; Montizaan et al., 2010; Brunello and Comi, 2015). Likewise, later retirement gives employers incentives to promote workers to higher occupational positions even at an advanced age if they expect them to remain with the company longer (Bertrand et al., 2020). On the contrary, there are also arguments against suspecting an impact of a prolonged work horizon on job promotions and wage trends. A longer working life can exacerbate health-related concerns (Barschkett et al., 2022; Bertoni et al., 2018), prompting workers to reduce professional responsibilities rather than take on additional tasks, in order to avoid occupational stress. Moreover, from the employer's point of view, uncertainty about individuals' actual retirement entry may prevent changes in promotion practices with respect to middle-aged or older workers. Hence, whether longer working lives lead to changes in career and wage trajectories ultimately remains an empirical question.

We empirically analyze the labor market consequences of career extensions on individuals who are still relatively far from retirement by exploiting quasi-exogenous variation in retirement entry age. In particular, the empirical analysis uses non-linear and cohort-specific variation in the expected work horizon caused by a German pension reform enacted in 2007. The reform raised the normal retirement age (NRA) incrementally from 65 to 67 years for all cohorts born after 1946, thereby increasing the expected working lifetime heterogeneously by one month to two years depending on year of birth. We quantify the effects of a longer working life on occupational mobility, professional advancement, and wage dynamics up to eight years after the reform on middle-aged workers, adopting a similar difference-in-differences design as Carta and De Philippis (2022). Our analysis takes advantage of the clear and unambiguous age cut-offs in German pension eligibility regulation, where the post-reform NRA depends exclusively on year of birth, and not on contribution length or on the continuity of the working life. We combine detailed representative survey data from the German Socio-Economic Panel (SOEP) and administrative records on work biographies from the Sample of Integrated Employment Biographies (SIAB) to measure the forward-looking effects of the 2007 reform on employment trajectories. Specifically, we define different measures of career advancement based on changes in the skill content of work from standardized occupational classifications and changes in the job level (Bayer and Kuhn, 2019; Klemt and Droßard, 2013; Zucco and Bächmann, 2020), and additionally construct wage-based measures of professional advancement from observed changes in wage rates and wage growth.

We find that an increase in retirement entry age increases upward occupational mobility, but we find no evidence of shifts in wage trends. A one year increase in the expected time to retirement (ETR) increases the probability of being promoted to a higher-ranked position by between 2.8 to 5.9 percentage points over a six year post-reform period. With

a baseline promotion rate of about nine percent per year, the effects involve a substantial increase relative to the pre-reform probability of getting promoted. In contrast, we find no evidence of a prolonged work horizon changing the wage trajectories of middle-aged workers. An increase in the ETR by one year is only associated with very small changes in hourly wage growth of about 0.1 percentage points that is statistically insignificant. Thus, any changes in promotion practices induced by delayed retirement entry do not seem to translate into pecuniary gains at least up to five years after the increase in retirement age was enacted.

We further evaluate the timing of the effects by employing event-study analyses, which reveal that promotion effects are quite uniformly distributed over the post-reform period and relatively persistent over time. Event study estimates also reaffirm that wage effects are small and statistically insignificant up to five years after the NRA was extended, with findings being robust to alternative model specifications controlling for differential pre-trends and winsorized wage data.

In analyzing the heterogeneity over subgroups, we find suggestive evidence indicating that promotion effects are at least in part explained by changes of employer. A comparison of within-company upward moves with upward moves that include company changes reveals that promotion effects are smaller if only within-company promotions are considered. One cautious interpretation is that employees' self-initiated professional advancement seems to be a stronger driving force behind the observed promotion effects relative to employers' active sponsorship of employees within the firm.

We conduct a set of robustness checks to assess the sensitivity of our findings to changes in the empirical specification, including extensions of the time horizon, sample conditions, and functional form assumptions, and document very consistent results over the alternative specifications. We also provide evidence that our findings are robust to concerns about sorting effects. Previous studies show that pension reforms affect labor supply choices, potentially altering the composition of the labor force (Gohl, 2022; Carta and De Philippis, 2022). We test if our results are robust to sorting effects by conditioning on pre-reform employment in our sensitivity analyses, and find similar results.

We further explore the robustness and the external validity of our main results by evaluating a second reform of the German public pension system which introduced sharp and discontinuous variation in the eligibility for early retirement among women. The reform, enacted in 1999, abolished the so-called 'pension for women' for all birth cohorts from 1952 onwards, thereby raising the minimum retirement age for women from 60 to 63 years (Barschkett et al., 2022; Geyer and Welteke, 2021; Fischer and Müller, 2020). We utilize the variation in employment histories after the reform between the adjacent 1951 and 1952 birth cohorts, aged between 43 and 55 in the survey period, to analyze if our main results replicate in a different context. We find that results for the 1999 reform are strongly aligned with our main findings. A three year increase in the ETR is associated with a 9.2 percentage points increase in the probability of getting promoted to a higher occupational position within the first seven years after the reform. This corresponds to an increase by about 3.1 percentage points for a one-year increase in the ETR, over a seven-year period. We also confirm small but insignificant effects of extending the work horizon on hourly wage growth, hence documenting similar patterns based on two different reforms of the German pension system as sources of identification.

From a policy perspective, our results are of interest for at least two reasons. First, we believe that the increase in occupational mobility during later stages of the career observed for both men and women facing a longer working horizon can have relevant implications for labor market and equal opportunities policies. Typically, interruptions in employment during family formation coincide with the most career-relevant years of professional establishment. Our findings suggest that foregone career advancement during early stages of the career can potentially be compensated to some extent in the later course of the working life when careers are extended. This is consistent with previous findings by Blundell et al. (2021), who show for the UK that women can at least partially compensate for the negative labor market effects of family-related career interruptions through increased training later on. In addition, improved opportunities for professional advancement in the second half of the working life may also incentivize men to share care-related tasks more equally with their partners in the beginning of their career, with potentially desirable effects on gender equality. Second, our findings indicate that there might be labor market frictions preventing pecuniary returns to improvements in the occupational position. From a policy perspective, an increase in wage growth through career advancement in the second part of the career would have important social policy implications (Scott et al., 2019). If older workers and individuals with previously low rates of career advancement could be integrated more strongly during the second half of their working lives, this could lead to higher life-time earnings and thus higher pension entitlements. However, our findings indicate that improvements in professional advancement for individuals with delayed retirement entry do not involve monetary returns at least in the medium run. Future research may investigate the obstacles inhibiting a stronger link between job promotions and wage returns.

We contribute to several strands of literature. First, we extend existing research on the forward-looking effects of delayed retirement entry on younger individuals by providing novel evidence of effects on occupational mobility and wage growth, whereas previous work establishes anticipatory effects of extending the work horizon on labor supply (Carta and De Philippis, 2022; Gohl, 2022; French et al., 2022; Geyer et al., 2020; Engels et al., 2017; Hairault et al., 2010), training (Gohl et al., 2021; Brunello and Comi, 2015; Montizaan et al., 2010), health behavior (Bertoni et al., 2018), and labor demand spill-overs (Bovini and Paradisi, 2019). Our paper also aligns with previous findings by Bertrand et al. (2020) showing that individual effort and promotions of middle-aged workers respond to changes in the duration of the working life. While Bertrand et al. (2020) study a select population of civil servants in India, we provide evidence in line with their findings for a representative sample of workers in Germany. Our work is also related to Ferrari et al. (2022) who show that Dutch employers respond to an increase in the NRA by delaying hiring, but their analysis focuses on the direct (and not the anticipatory) effect for workers close to retirement.

The remainder of the paper is organized as follows: Section 4.2 describes the German pension system and the 2007 pension reform; Section 4.3 presents the empirical strategy and the data; Section 4.4 reports the main results; Section 4.5 presents the robustness analyses including results for the 1999 pension reform; and Section 4.6 concludes.

4.2 Institutional Context

4.2.1 The German Public Pension System

The German public pension system covers about 85 percent of the working population and is the largest provider of old-age insurance in Germany (DRV, 2021).[2] Public pensions constitute one of three pillars of the German pension system, but compared to the public pensions, the other two pillars (occupational pensions and private provisions) play relatively minor roles (Geyer and Welteke, 2021; Carta and De Philippis, 2022). The public pension system is financed as a pay-as-you-go scheme by compulsory social insurance of the working population who pay a considerable fraction of their monthly gross income as contributions.[3] The amount of old-age pension receipts is strongly linked to the total contributions an individual paid over their entire working life. Individuals are entitled to an old-age pension upon reaching the statutory retirement age, with permanent deductions for early retirement and increases for late retirement.[4] Exemptions and special rules exist for individuals with long-term insurance exceeding 35 years.[5] Apart from early retirement, disability pensions, temporary unemployment or partial retirement are or have been possible pathways to retirement (Geyer and Welteke, 2021). However, the majority of the working population cannot expect to retire via a pathway that is not affected by changes to the statutory retirement age.

4.2.2 The 2007 Pension Reform

In 2007, the statutory retirement age in Germany was increased incrementally from 65 to 67 years. The 2007 reform was a central part of the German reaction to growing demographic pressures on the pension system. The increase in the normal retirement age (NRA) was highly debated, and even years after the implementation of the law, it is still contested by parts of the established political spectrum (Brussig et al., 2016, p.50). The 2007 reform raised the NRA for all cohorts born after 1946, thereby affecting all individuals aged 60 or younger. Only individuals with more than 45 years of contributions were exempted from the increase.[6] Starting with the 1947 birth cohort, the NRA was increased gradually and non-linearly from 65 years to 67 years: For cohorts born between 1947 and 1958, the NRA was increased by one additional month per birth year, for cohorts born between 1959 and 1964 the NRA was increased by two additional months per birth year (see Figure 4.1). The 1964 cohort will be the first to retire at 67 years in 2031. Hence, for cohorts born in 1964 or later, who were aged 43 or younger at the time of the reform, the reform increased the expected time to retirement by two full years (24

[2]Self-employed individuals are not covered by compulsory public pension insurance but they can contribute voluntarily conditional upon proving a certain minimum income. Civil servants and certain professional classes have separate old-age insurance systems.

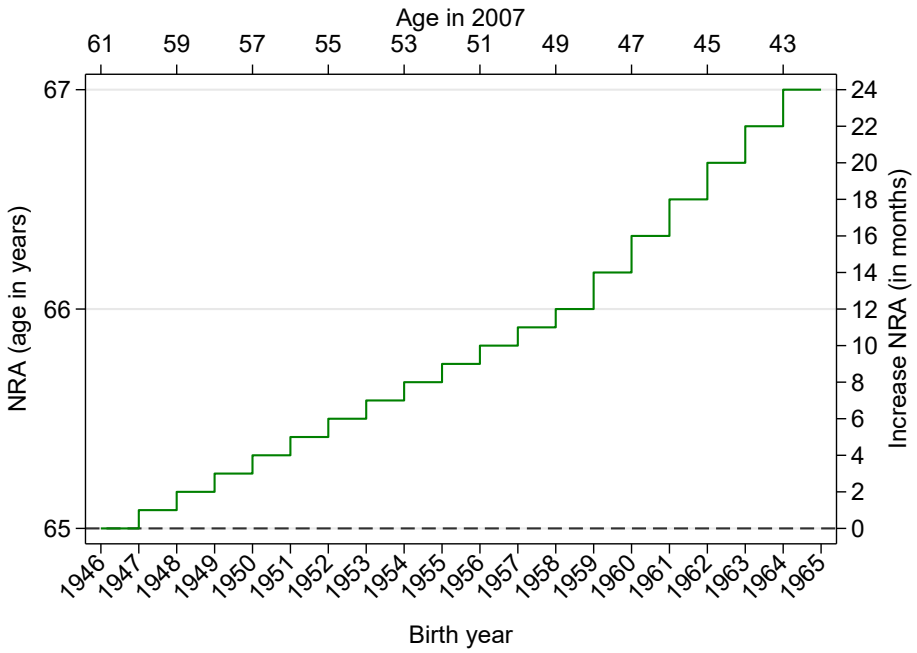
[3]As of 2022, the contribution rate is 18.6 percent of gross income, shared equally by employees and employers. The public pension scheme contribution rate varied between 18.6 and 19.9 percent between 2000 and 2022.

[4]Benefits are reduced by 0.3 percent (increased by 0.5 percent) over the entire duration of the pension spell per month of early (delayed) benefit collection.

[5]Prior to the 2007 reform, individuals with at least 35 years of contributions could collect benefits without deductions at the age of 63. Between 2007 and 2014, the especially long-term insured with at least 45 contribution years could collect full benefits at the age of 65.

[6]For individuals with more than 45 contribution years, the NRA remained at 65 years, which marked the first time that this distinction was made on the basis of the number of contribution years.

months).



Notes: The plot shows the normal retirement age (NRA) in years in the German public pension system after the 2007 reform (left axis), as well as the associated change in the expected time to retirement in months relative to the pre-reform period (right axis). The dashed horizontal line indicates the NRA prior to the 2007 reform, which continues to correspond to the NRA for individuals with more than 45 years of pension contributions until 2014.

Figure 4.1: The 2007 Reform of the Normal Retirement Age in Germany

4.3 Research Design

4.3.1 Identification Strategy

We estimate the forward looking effects of an increase in the expected working lifetime on career trajectories based on a Difference-in-Differences (DiD) inspired design. Adopting a similar approach as Carta and De Philippis (2022), we implement a DiD estimator with a multi-valued treatment variable capturing the change in the expected time to retirement (ETR) induced by the 2007 pension reform as our key explanatory variable. Our outcome variables of interest are job promotions and hourly wage trajectories, described in detail in Section 4.3.3. The quasi-exogenous cohort-specific variation in the expected retirement age induced by the reform allows us to estimate the magnitude of the forward looking effects of working longer on promotions and wage growth.

Formally, we estimate the following regression equation

$$Y_{it} = \beta_0 + \beta_1 \Delta ETR_c \times post2007_t + \beta_2 X'_{it} + \alpha_c + \gamma_a + \epsilon_{it} \tag{4.1}$$

where Y_{it} is the outcome variable of interest, ΔETR_c is the time-invariant cohort-specific difference in the expected retirement age between the post- and the pre-reform rule, i.e. $ETR_{post2007} - ETR_{pre2007}$, denoted in years, and $post2007$ is a binary variable indicating the post reform period.[7] The coefficient β_1 is the coefficient of interest capturing the impact of a one year increase in the expected retirement age after the introduction of the reform. We include cohort fixed effects, α_c, to absorb cross-sectional pre-reform differences in the outcome variable between cohorts, and age fixed effects, γ_a, to account for declining wage-age profiles (see Section 4.3.4 for a discussion of age trends). X_{it} are individual-level covariates controlling for personal and employer characteristics.[8] In the main analyses, we pool observations into a pre-treatment and a post-treatment period, hence the coefficient of interest β_1 gives the overall response to a longer working horizon over the entire post-treatment period. We further implement an alternative specification similar to an event study with year fixed effects and treatment-time interactions for every observation period to study the timing of the response, but we defer the details of this model to the Appendix (Section D.1.2).

In DiD estimation with a continuous or multi-valued treatment variable, the average treatment effect of a positive treatment dose is identified if the strong parallel trends assumption is fulfilled (Callaway and SantAnna, 2021), requiring that the average change in outcomes over time for individuals who received a certain treatment dose is the same as if all individuals had been assigned that dose of treatment.

Whether the strong parallel trends assumption holds cannot be tested formally, but its plausibility is evaluated in Section 4.3.4. Further identifying assumptions are the independence of treatment status with respect to the potential outcomes (Keele, 2015), as well as the stable unit treatment value assumption, SUTVA (Wooldridge, 2010). With treatment status being determined by year of birth, we argue that the former assumption is fulfilled since there is no evidence that adjacent birth cohorts react inherently differently to an increase in the ETR when controlling for age. The SUTVA requires that the treatment status of one unit does not influence the potential outcomes of other units. In general, it could be possible that increases in promotions or wage raises among one birth cohort could have spill-over effects to other age cohorts, who may face a decrease in promotion rates. In Section 4.3.4, we provide evidence suggesting that the SUTVA is not violated in the present context.

4.3.2 Data and Sample

The empirical analyses are based on two data sets, the German Socio-Economic Panel (SOEP) and the Sample of Integrated Employment Biographies (SIAB).[9] Both data sets contain individual-level information about the full employment trajectory, including information on earnings and occupational position, which we use to construct the central

[7] The minimum ΔETR is 0.583 years (seven months) for the oldest cohort in the sample born in 1953; the maximum ΔETR is two years for the youngest cohort born in 1964.

[8] Specifically, we control for gender, immigrant background, region, college education, a quadratic in work experience, company size and sector.

[9] We gratefully acknowledge access to the SOEP data (SOEP, 2019) provided by the Research Data Center of the Socio-Economic Panel (FDZ SOEP), as well as access to the SIAB data base (Antoni et al., 2019a) and the SIAB data documentation (Antoni et al., 2019b) provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

outcome variables. The data sets differ in terms of data collection, occupational and socio-demographic characteristics, and sample size. We use both the SOEP and the SIAB data to combine the strengths of each data source, described in more detail below.

The German Socio-Economic Panel (SOEP) The SOEP is a representative longitudinal survey of private households in Germany. Surveying around 30,000 individuals in approximately 15,000 households each year, it is the largest and most comprehensive panel study in Germany (Goebel et al., 2019). It comprises individual employment biographies, as well as a wide range of personal and household level characteristics. Interviews are conducted face-to-face by trained interviewers using computer-assisted personal interviewing (CAPI). Besides containing information on gross labor income, the SOEP also surveys weekly hours worked, facilitating the calculation of hourly wage rates. In addition, it features a wide range of occupational and job characteristics, including current occupational position and skill level, which we use to construct job promotion indicators. In the empirical analyses, we use survey years 2000 to 2017 from SOEP release v36. Sample conditions are described below.

The Sample of Integrated Employment Biographies (SIAB) The SIAB is a large administrative data set comprising a two percent random sample of all individuals in Germany who are subject to social security contributions, marginally employed, registered as job seekers, receiving unemployment benefits or participating in active labor market policies. For individuals in employment, it contains information on the gross daily wage, the current occupational status and the required skill level of the current position as reported by the employer, as well as basic socio-demographic indicators. Given the large number of observations, the SIAB data are well suited to compute precise estimates at the cohort level. However, the SIAB does not contain information on hours worked, preventing an analysis of hourly wages and wage growth. In the empirical analyses, we take advantage of the large cohort-specific sample size of the SIAB to evaluate the plausibility of our identifying assumptions.

Sample definition The empirical analyses are based on a sample of full-time or part-time employed workers aged below 60 from the 1953-1964 birth cohorts. Individuals above the age of 60 are excluded because employment starts to decline more strongly for these age groups, which could lead to self-selection bias when estimating the reform effects.[10] We restrict the sample to cohorts born between 1953 and 1964 in the main analyses because of a change in early retirement regulation affecting cohorts born before 1953.[11] However, we utilize the exogenous variation in early retirement incentives between the 1951 and the 1952 cohorts in the robustness analyses. Likewise, we restrict the time horizon and only consider the years 2000-2013 in the main part of the analyses because

[10] Restricting the sample to individuals below age 55 does not change the magnitude of the main effects, but reduces statistical power, hence we refrain from excluding more of the older cohorts.

[11] Cohorts born before 1953 were affected by two additional reforms of the German pension system which changed the incentives for early retirement. Specifically, the 1999 pension reform abolished the so-called 'old-age pension for women' for women born after 1951, leading to significant employment effects (Geyer et al., 2020; Geyer and Welteke, 2021). Moreover, individuals born before 1952 could claim pension benefits (with deductions) before reaching the NRA through the 'old-age pension for the unemployed' or after partial employment due to age. Both of these regulations led to a cut-off in retirement incentives between the 1951 and 1952 birth cohorts, significantly affecting the ETR for a significant share of these cohorts.

two additional reforms of the German pension system were implemented in 2014, but we study the implications of extending the time horizon beyond 2013 in the sensitivity analyses.[12] The sample excludes civil servants and self-employed individuals who are generally ineligible for statutory pension insurance, as well as individuals in the military and in training. Individuals with missing information in key explanatory variables are also excluded. In the SOEP survey, wage information is collected every year, but information on ISCO skill levels required to measure job promotions is not surveyed annually (see Section 4.3.3 for details on measuring promotions).[13] Hence, job promotions are only measured in selected years, whereas wage rates are computed annually. As a result, sample sizes differ between the promotions and wage outcomes in the main analyses, but we also compute the main estimates for a common sample in the sensitivity section.

4.3.3 Measuring Career Advancement

To analyze the effects of a prolonged work horizon on career trajectories, we define different measures capturing occupational advancement. Following previous literature, we derive our primary indicator of job promotions based on changes in the skill content of work from standardized occupational classifications (Zucco and Bächmann, 2020; Matthes and Vicari, 2017). As a second measure, we follow Klemt and Droßard (2013) and Bayer and Kuhn (2019), and identify job promotions based on changes in job levels. Finally, we construct wage-based measures of occupational advancement from observed changes in hourly wage rates and wage growth.

Promotions Using ISCO Skill Levels The first promotion indicator is based on changes in the skill level that is typically associated with a particular occupational position. Specifically, we utilize the International Standard Classification of Occupations 1988 (ISCO-88) which defines four different skill levels, from one (lowest) to four (highest).[14] For eight out of ten major occupational ISCO groups, the associated skill level is unambiguous (Table D.1). For example, 'Services and Sales Workers' are assigned to skill level two, whereas 'Technicians and Associate Professionals' are assigned to skill level three. The group of 'Managers' can either be classified as skill level three or four, hence, we classify managers with a leadership position as level four, and managers without leadership responsibilities as level three. The tenth group ('Armed Forces', covering skill levels one,

[12] In 2014, the retirement age at which pension benefits could be claimed without deductions was lowered by up to two years for the especially long-term insured with more than 45 years of pension contributions. According to Keck and Krickl (2018), this affected 38.5 percent of men and 28.5 percent of women among the contributors to the pension system. A second reform implemented in 2014 introduced the pension for mothers ('Mütterrente'), increasing the pension wealth of mothers with children born before 1992. Since this reform affected (older) cohorts more strongly that, on average, had more children before 1992, including the post-2014 period might bias the results.

[13] Specifically, the SOEP only implements a partial survey on the current occupational position in 2001, 2003, 2005, 2006, 2008, 2010, and 2012. In the partial survey years, only individuals who report a job change are asked to fill out the question on the current occupational position. For all other individuals, the information from the previous year is used, leading to improbably low numbers of promotions in the partial survey years. Hence, we do not use the information from the partial survey years when analyzing the promotion outcomes.

[14] The four ISCO skill levels correspond to the formal educational levels required for a particular position, as defined by the International Standard Classification of Education (ISCED): basic education (level one, unskilled workers), secondary education (level two, skilled workers), post secondary education (level three, skilled professionals), and tertiary education (level four, academic professions).

two, and four) is excluded from the analyses in the present paper. We then define the job promotion indicator as a binary variable which takes the value of one if an individual's current skill level is higher than the skill level in the previous observation period, and zero otherwise. Contrary to Zucco and Bächmann (2020) who consider only promotions within a firm, we refer to all upward moves in the occupational position as a promotion, irrespective of whether they happen inside or between companies. Job switching itself can be considered as a form of human capital investment (Bayer and Kuhn, 2019), and labor market mobility towards other employers coinciding with upgrades in the skill level arguably reflects some form of career advancement. In our robustness analyses, we further study the implications of using a narrower definition of job promotions excluding company changers. One disadvantage of defining promotions from ISCO skill levels is the strong correspondence between skill levels and the formal educational requirement associated with a particular occupational position. Changes in occupational skill levels thus tend to occur only after an individual pursued further training, while more subtle aspects of career advancement are not captured with this promotions indicator. We define an alternative measure of job promotions utilizing changes in the associated job complexity, described next.

Promotions Using Job Levels A second measure of promotions utilizes the classification of job levels based on Klemt and Droßard (2013), also used by Bayer and Kuhn (2019). This approach uses information on the complexity, the autonomy, and the responsibility of job tasks to construct five job levels: untrained, trained, associate, professional, and managerial. Again, a dummy variable is computed to indicate whether the job level increased since the last observation period. Besides relying less on the formal education required to perform a specific job position, this promotions indicator is arguably more comparable across different occupations relative to the definition based on skill levels. However, it is quite specific to the German system and, thus, less comparable to other contexts.

Wage-based Measures Finally, we measure career advancement directly through changes in hourly wage growth.[15] Wage-based measures are more likely to capture even subtle changes in an individual's occupational position or bargaining power, but permit only limited insights about the underlying mechanism explaining the upward move. Moreover, not all occupational upward moves coincide with changes in hourly wage rates, so it is of interest to study formal promotions and wage growth in separation. To quantify wage growth, we use data on gross monthly labor income converted to real terms based on the consumer price index (base year 2015), and calculate hourly wage rates from weekly hours worked. We use contractually agreed working hours whenever available, and actual hours including overtime otherwise.[16] For some parts of the analyses, hourly wages are winsorized at the five percent level. We study the changes in hourly wage rates induced by the 2007 reform in levels, as well as changes in annual wage growth rates.

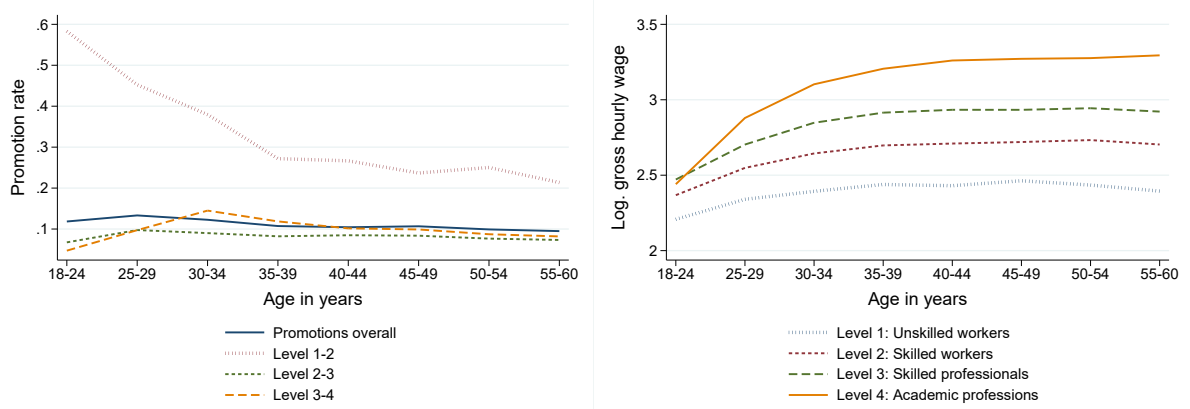
[15]Hourly wages can only be constructed using the SOEP data, because the SIAB does not contain information on hours worked.

[16]See Dütsch et al. (2019) for a discussion of the pros and con's of using actual and contractual hours worked with SOEP data.

4.3.4 Descriptive Evidence

Promotions and Wage Growth over the Life-Cycle

In Figure 4.2, we provide descriptive empirical evidence about average job promotion and wage profiles over the course of the entire working life. Hourly wage growth is steepest in the beginning of the career, flattening out when workers reach their 40s, with substantial level differences depending on the skill level of the current job (Figure 4.2b). Job promotion rates vary less over age, except for unskilled workers who are more likely to move on to higher occupational positions in the first part of their employment career in comparison to later periods (Figure 4.2a).



(a) Job Promotions

(b) Gross Hourly Wages

Notes: The plots show the proportion of workers who were promoted to a higher occupational position relative to the previous observation period by ISCO skill level over age (panel a), as well as the evolution of hourly wage rates by level of the current job over age (panel b). Data Source: SOEP v36, 2000-2017.

Figure 4.2: Job Promotion and Wage Profiles by ISCO Skill Level over the Life-Course

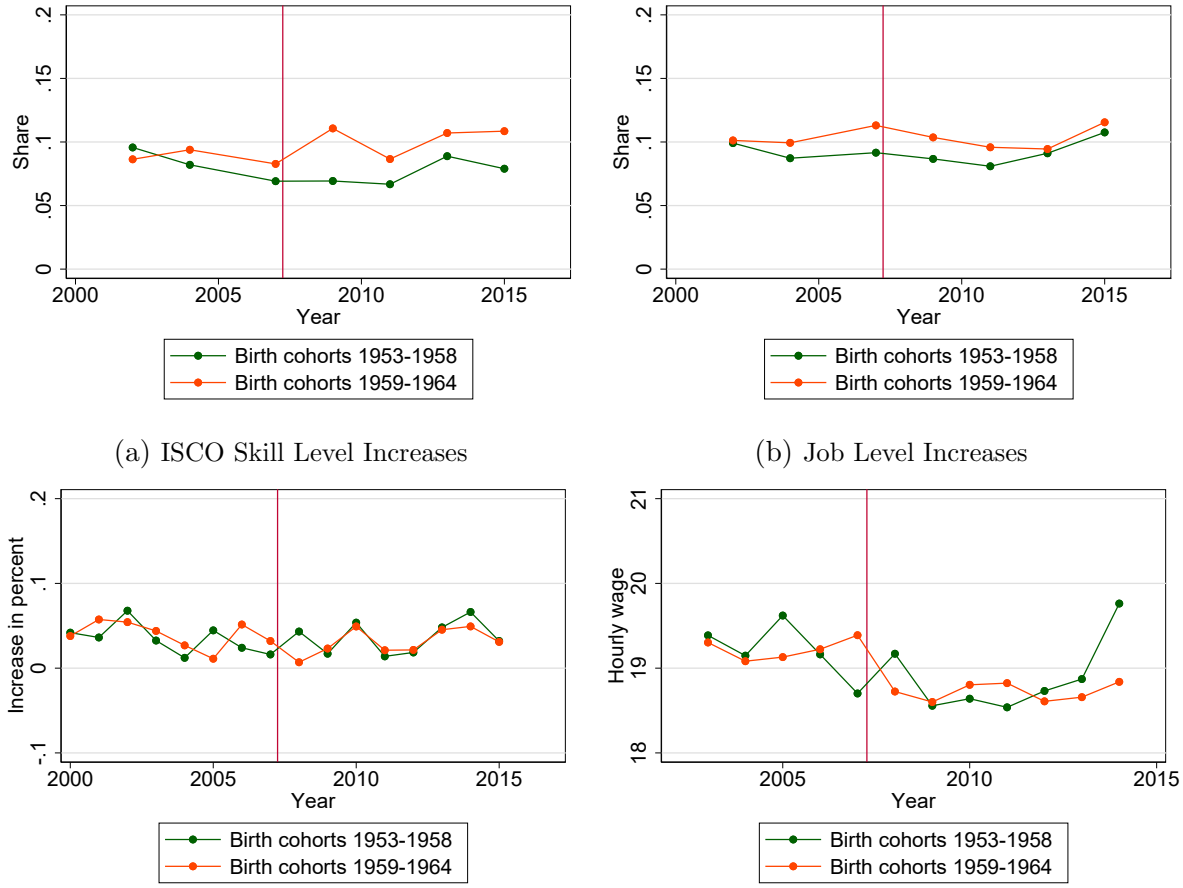
In the sample of 40 to 60 year old workers, promotion rates are relatively stable over age in the pre-reform period (Figure D.6). On average, between eight and ten percent of workers reach a higher occupational position every period, based on changes in the ISCO skill level (Figure D.6a). Promotion rates are slightly higher when computed based on the job level, with transition rates of about ten to 12 percent (Figure D.6b). The probability of getting promoted decreases with the level of the current job, with lower promotion rates among workers occupying higher occupational positions (Figure D.5). The share of individuals getting promoted does not change significantly with age in the sample of 40 to 60 year old workers.

In contrast, hourly wage growth decreases with age in the sample of 40 to 60 year old workers (Figure D.6c). Annual wage increases average at about four percent among 40-year old workers, gradually decreasing afterwards to about two percent per year when workers reach age 55.[17] To account for age trends in hourly wage growth in our empirical analyses, we therefore include age fixed effects in all regressions using wage outcomes.

[17]Declining wage profiles over the life course are also documented in previous literature, for example by Schrenker and Zucco (2020) who estimate wage profiles that peak between age 45 and 50 years before they start to decline.

Supporting Evidence of the Identifying Assumptions

To examine the plausibility of the parallel trends assumption we use graphical analyses, dividing individuals into two groups who were differentially affected by the 2007 reform: birth cohorts 1953-1958 who faced only a small increase in the NRA of 7-12 months ('weakly treated'), and birth cohorts 1959-1964 who faced a larger increase in the NRA by 14-24 months ('strongly treated'). We then depict the pre- and post-reform trends in the key outcome variables for the weakly and the strongly treated birth cohorts in Figure 4.3. Figure D.7 in the Appendix repeats the same analyses based on a finer differentiation into cohort groups.



(a) ISCO Skill Level Increases

(b) Job Level Increases

(c) Hourly Wage Increase

(d) Hourly Wages

Notes: The plots show the evolution of the key outcome variables before and after the 2007 reform for cohort groups who were differentially affected by the increase in the NRA, birth cohorts 1953-1958 (weakly treated, $<$ 12 months increase) and birth cohorts 1959-1964 (strongly treated, 14-24 months increase). Promotions are defined as changes in the ISCO-88 skill level (panel a) or the occupational job level (panel b) relative to the last observation period, hourly wages are measured in percent changes (panel c), or in Euro amounts (panel d). The vertical red line markes the time of the 2007 reform. The sample includes employed workers born between 1953-1964. Data Source: SOEP v36, 2000-2015.

Figure 4.3: Graphical Evidence of Parallel Trends

Promotion rates (defined based on ISCO skill levels) evolve in parallel for weakly and strongly treated groups in the pre-reform period up to 2007 (Figure 4.3, panel a). For

promotions using job levels, the parallel trends assumption is not visibly violated either (Figure 4.3, panel b). There are no differing trends in promotions by age that would make a violation of the parallel trends assumption likely (Figure D.6), and there were no other reforms of the German pension system in the pre-reform time period. In contrast to promotion rates, hourly wage rates and wage growth do not exhibit obvious parallel trends but instead seem to diverge with distinct patterns between 2005 and 2008. However, alternative estimates based on event-study analyses do not show significant differences in pre-trends for any of the outcome variables, including the wage outcomes (Figure 4.4). Nonetheless, the estimates for the wage outcomes should be interpreted with some caution, and we will further test the plausibility of the parallel trends assumption. Moreoever, we acknowledge that the use of a multi-valued or continuous treatment variable generally requires the stronger parallel trends assumption to hold (Callaway and SantAnna, 2021). There is no evidence that the different birth cohorts inherently react differently to certain levels of increases in the ETR occurring through the reform. We thus assume that the strong parallel trends assumption holds to the same extent as the normal parallel trends assumption, although this cannot be tested formally.

We further examine the plausibility of the stable unit treatment value assumption (SUTVA) in the present context. A priori, increases in promotions or pay raises among one cohort induced by the reform could have negative spill-over effects to other age cohorts. But two empirical facts, if put together, do not support this hypothesis: Promotions do not decrease with age in the pre-reform period (Figure D.6), and there are no negative cohort-specific trends in promotions for the control group (Figure D.7). Assuming that in absence of the reform, promotion rates would have remained at a similar level to the pre-reform period, negative spill-over effects should lead to a downward sloping time trend for the weakly treated cohorts. Given that we do not observe such a negative time trend, it seems unlikely that promotions among the weakly treated cohorts decreased due to an increase in the ETR among the strongly treated cohorts.

In Appendix D.2.4, we provide additional supporting evidence of the identifying assumptions, further showing that adjacent cohorts do not differ in key characteristics prior to the reform (Table D.2).

4.4 Results

4.4.1 Promotion Effects

We find robust empirical evidence for a causal effect on job promotions of raising the normal retirement age. Depending on the specification, the probability of getting promoted increases by between 2.8 to 5.9 percentage points if the expected time to retirement (ETR) is increased by an additional year (Table 4.1). With a baseline promotion rate of about nine percent, the effects correspond to an increase by five to 11 percent over the 2008 to 2013 period relative to the pre-reform probability of getting promoted.

In more detail, we estimate three different model specifications for two promotion measures, using Difference-in-Differences (DiD) inspired regressions with a multi-valued treatment variable capturing the increase in the ETR in years (Section 4.3.1). All regressions pool observations into a pre-treatment and a post-treatment period and are estimated

Table 4.1: Pooled Promotion Effects

	Skill level increases			Job level increases		
	(1)	(2)	(3)	(4)	(5)	(6)
Increase in ETR × 2008-2013	0.028**	0.054***	0.059***	0.032***	0.037*	0.021
	(0.011)	(0.018)	(0.022)	(0.012)	(0.020)	(0.024)
Pre-reform mean	0.09	0.09	0.09	0.098	0.098	0.097
Observations	13,347	13,347	10,144	11,081	11,081	8,115
Age FE	N	Y	Y	N	Y	Y
Industry FE	N	Y	Y	N	Y	Y
W/o manufacturing	N	N	Y	N	N	Y

Notes: SOEP v36 (2000-2013). Promotion effects for employed individuals of birth cohorts 1953-1964. DiD estimates with controls for gender, migration background, region (East/West), college education, experience, experience squared, company size, and sector (public/private). In columns 3 and 6, individuals who worked in manufacturing in 2007 are excluded. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01.

using linear probability models (LPM).[18] In columns 1-3 in Table 4.1, promotions are defined based on changes in the ISCO skill level, columns 4-6 show results with a promotion measure based on occupational job levels. In the baseline specification which includes individual-level controls (columns 1, 4), an increase in the ETR by one year is associated with a 2.8-3.2 percentage point increase in the probability of being promoted ($p<0.05$). The findings are comparable (albeit slightly larger) in an alternative specification that additionally includes age and industry fixed effects (columns 2, 5). Specifically, coefficient estimates indicate a treatment effect of 5.4 percentage points for promotions based on skill levels ($p<0.01$), and an effect of 3.7 percentage points for promotions based on job levels (but no longer $p<0.1$). A third specification further excludes observations who worked in the manufacturing sector in 2007, which was most heavily affected by the Great Recession coinciding with the post-reform period (columns 3, 6). Results are very similar in the specification based on skill levels, but smaller and insignificant with promotions based on job levels. We analyze the impact of excluding the manufacturing sector in more detail in the robustness analyses in Section 4.5.1.

4.4.2 Effects on Wage Growth

While we find significant effects of raising the ETR on job promotion rates, we find no evidence of a prolonged work horizon changing wage trajectories. An increase in the ETR by one year is only associated with very small changes in hourly wage growth of about 0.1 percentage points that is statistically insignificant at any conventional significance level.

Specifically, we estimate similar DiD regressions with hourly wage changes as the dependent variable (Table 4.2). Given that hourly wage growth varies by age, and because the cohorts are of different ages at the time of the reform, age fixed effects are included in

[18] We present estimates based on logistic regressions in our robustness analyses in Section D.2.9. Besides estimating pooled regressions with a pre- and a post-reform period, we present estimates from event study models in Section 4.4.3 to analyze treatment effects over time.

Table 4.2: Pooled Wage Effects

	Hourly wage increases		
	(1)	(2)	(3)
Increase in ETR × 2008-2012	0.009	0.012	0.009
	(0.022)	(0.022)	(0.010)
Pre-reform mean	0.048	0.048	0.035
Observations	30,784	30,784	30,784
Age FE	Y	Y	Y
Industry FE	Y	Y	Y
Different pre-trends	N	Y	N
Winsorized data	N	N	Y

Notes: SOEP v36 (2000-2013). Wage effects for employed individuals of birth cohorts 1953-1964. DiD estimates with controls for gender, migration background, region (East/West), college education, experience, experience squared, company size, and sector (public/private). In column 3, the outcome variable is winsorized at the 5% level. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01.

all three specifications of the model, alongside industry fixed effects and individual level controls. Column 2 additionally controls for differing pre-trends (see Appendix D.1.2 and Dustmann et al. (2022)), since the graphical analyses have shown that hourly wage increases exhibit non-parallel trends prior to the reform. Column 3 further uses winsorized hourly wage data to control for outliers in the wage distribution. In all three specifications, coefficient estimates of the reform effect are very small and statistically insignificant. We will provide further evidence about the underlying mechanisms and heterogeneous treatment effects in the next Section. However, based on the empirical results from this Section, we conclude that any increases in job promotions that the reform might have caused did not seem to translate into hourly wage gains up to five years after the reform.

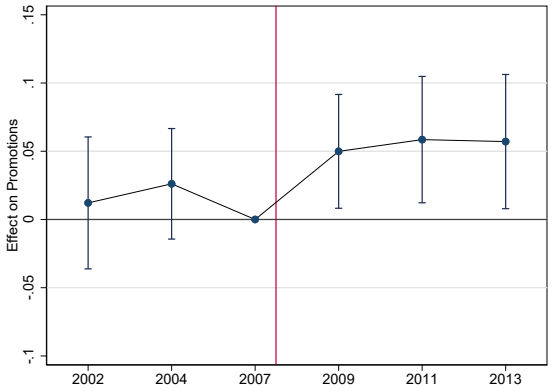
4.4.3 Mechanisms and Heterogeneous Effects

Effects over Time

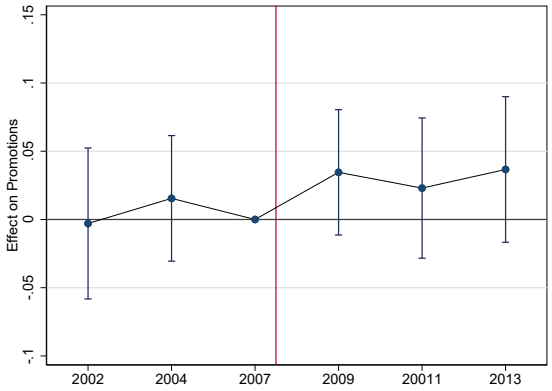
In this Section, we analyze the impact of the 2007 reform within an event study design, allowing us to examine the timing of the underlying effects. Instead of pooling all estimates into one pre- and one post-treatment period, we estimate treatment-time interaction terms for every observation period. Time fixed effects are included in the form of year fixed effects, and a separate treatment effect coefficient is identified for every observed time period. Appendix D.1.2 presents the event-study model more formally. Results are depicted graphically here in Figure 4.4, Table D.3 in the Appendix shows the corresponding coefficient estimates. All regressions include age group and industry fixed

effects, as well as individual level controls.[19]

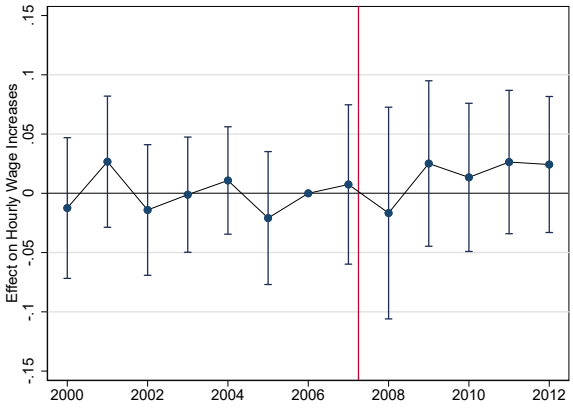
(a) Promotion Effects Using Skill Levels



(b) Promotion Effects Using Job Levels



(c) Effects on Hourly Wage Growth



Notes: The plots show event study estimates with 95 percent confidence intervals of an increase in the ETR on promotions using ISCO-88 skill levels (panel a), promotions using job levels (panel b) and hourly wage increases (panel c) over time. The vertical red line indicates the time of the 2007 reform. Estimates based on employed individuals born between 1953-1964. Data Source: SOEP v36, 2000-2013.

Figure 4.4: Effects of the 2007 Reform on Promotions and Wage Growth over Time

Event study estimates confirm that raising the NRA causally increases job promotions, further revealing that effects are relatively persistent over time. A permanent increase in the ERA is associated with a permanent increase in the probability of getting promoted at least until the age of 60 (Figure 4.4, panels a-b). For both measures of job promotions, the effect of the reform is quite uniformly distributed over the 2008-2013 period, where coefficient estimates are slightly smaller and less precisely estimated in the specification based on occupational job levels compared to the ISCO-based classification.[20] These

[19]The inclusion of birth cohort and year fixed effects does not permit the inclusion of age-in-years fixed effects because this would induce perfect multicollinearity. Instead, we follow Levin and Stephan (1991) and others, dividing individuals into age groups in 5-year intervals, and include age group fixed effects to account for declining wage-age profiles.

[20]Differences between the two promotion concepts are not driven by differences in the sample, as shown in an additional robustness check in Appendix D.2.12.

findings are interesting for at least two reasons. First, they indicate that promotion effects do not depend on age. If the promotion effect differed for younger and older cohorts, the effect would visibly diminish over the years, as more of the younger cohorts would cross a hypothetical cut-off age threshold at which promotions became significantly less likely. Second, the uniformly distributed timing of the promotion effect eases the concern that observed differences in promotions are explained by the Great Recession which affects age cohorts differently. If this was the case, the promotion effect would also visibly taper off over time, contrary to what we observe.

Event study estimates also reaffirm that wage effects are small and statistically insignificant up to five years after the NRA was extended (Figure 4.4, panel c). These findings are robust to different model specifications controlling for differential pre-trends and winsorized hourly wage data.

Finally, the event study estimates provide additional supporting evidence of the identifying assumptions. Coefficients close to zero in the pre-reform period support the plausibility of the parallel trends assumption. Based on this criterion, parallel trends are confirmed for all three outcome variables. While the pre-reform period seems somewhat noisier for the wage outcome, the estimated effects are not significantly different from zero, irrespective of whether differential pre-trends are included.

Subgroup Analysis

In this Section, we explore whether the effects of the 2007 pension reform vary along demographic and socio-economic dimensions to test for heterogeneous treatment effects. In comparison to the baseline regression, additional interaction terms with the subgroup indicator are included (Gruber, 1994). In determining these groups, it is important to choose characteristics that are determined pre-reform in order to avoid "bad controls" (Angrist and Pischke, 2009; Cinelli et al., 2021).

Using event study analyses and difference-in-differences estimation, we document that effects are mostly homogeneous across different subgroups. However, we find suggestive evidence that promotion effects are at least in part explained by changes of employer. Comparing within-company upward moves and upward moves including company changes reveals that the effects of the 2007 pension reform are smaller if only within-company promotions are considered. Hence, we conjecture that employees' motivation and effort to seek professional advancement seems to be a stronger driving force behind the observed promotion effects than employers' active sponsorship of employees within the firm after the NRA increase, although additional supporting evidence would be useful.

Tables 4.3 and 4.4 present results for the main promotion measure based on ISCO skill levels. Appendix D.2.6 contains the corresponding estimates for alternative outcome variables, as well as additional graphical evidence. In Table 4.3, we study how the effects of the 2007 reform vary by demographic characteristics. Specifically, we investigate heterogeneous responses by gender, region and immigrant background. In all specifications, the main reform effect remains sizeable and significant, but there is only little evidence of heterogeneous responses along subgroups. For instance, we show that an additional year in the ETR is associated with a 6.6 percentage points higher probability of promotion for women ($p<0.01$), and while the effect appears to be smaller for men (-2.3 p.p.), the respective coefficient estimate of the interaction term is statistically insignificant

Table 4.3: Promotion Effects by Demographic Characteristics

	Skill Level Increases		
	(1)	(2)	(3)
Post-reform $\times\Delta ETR$	0.066***	0.055***	0.053***
	(0.022)	(0.019)	(0.019)
Post-reform $\times$			
Gender (1 = male)	0.006		
	(0.016)		
Post-reform $\times\Delta ETR$			
$\times$ Gender	-0.023		
	(0.021)		
Post-reform $\times$			
East Germany		0.005	
		(0.019)	
Post-reform $\times\Delta ETR$			
$\times$ East Germany		-0.005	
		(0.025)	
Post-reform $\times$			
Mig. Backgr.			-0.014
			(0.025)
Post-reform $\times\Delta ETR$			
$\times$ Mig. Backgr.			0.005
			(0.030)
Observations	13,347	13,347	13,347
Pre-reform mean	0.09	0.09	0.09

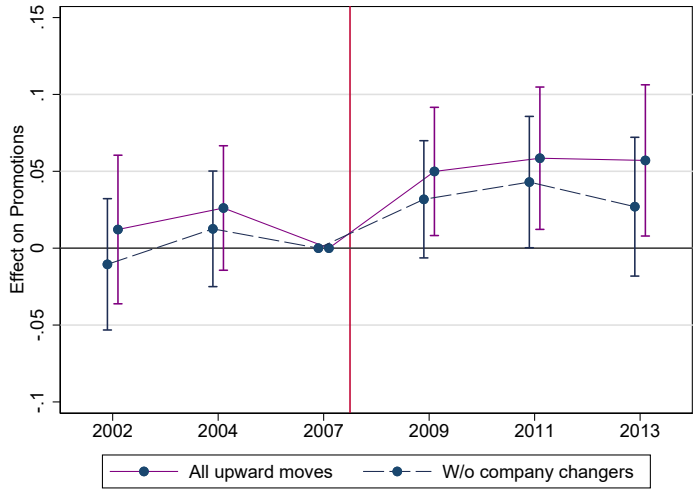
Notes: SOEP v36 (2000-2013). Promotion effects using skill levels for employed individuals of birth cohorts 1953-1964. Including triple interaction terms for gender (column 1), region (East/West, column 2) and migration background (column 3). Controls include gender, migration background, region, college education, experience, experience squared, company size, and sector. Age and industry fixed effects are included. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01.

Table 4.4: Promotion Effects by Socio-Economic Characteristics

	Skill Level Increases		
	(1)	(2)	(3)
Post-reform $\times\Delta ETR$	0.061**	0.068**	0.062***
	(0.024)	(0.027)	(0.021)
Post-reform $\times$			
Education (1 = No college)	0.023		
	(0.018)		
Post-reform $\times\Delta ETR$			
$\times$ Education	-0.011		
	(0.023)		
Post-reform $\times$			
High 2007 Labor Inc.		-0.003	
		(0.020)	
Post-reform $\times\Delta ETR$			
$\times$ High 2007 Labor Inc.		-0.024	
		(0.025)	
Post-reform $\times$			
Large Company			0.009
			(0.016)
Post-reform $\times\Delta ETR$			
$\times$ Large Company			-0.017
			(0.021)
Observations	13,347	11,079	13,347
Pre-reform mean	0.09	0.087	0.09

Notes: SOEP v36 (2000-2013). Promotion effects using skill levels for employed individuals of birth cohorts 1953-1964. Including triple interaction terms for education (column 1), 2007 gross labor income (column 2) and company size (column 3). Controls include gender, migration background, region, college education, experience, experience squared, company size, and sector. Age and industry fixed effects are included. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01.

(p> 0.1). Similarly, promotion effects of the pension reform are smaller for individuals with an immigrant background (-0.014), but insignificantly so. Promotion effects are also virtually identical in Eastern and Western Germany. In studying effect heterogeneity along socio-economic dimensions, the overall picture of uniform treatment effects is further confirmed (Table 4.4). Reform effects do not appear to vary systematically by individuals' level of education, their pre-reform income, nor the size of the company they work for. However, to further investigate the importance of employer characteristics, we conduct an additional analysis in which we separately look at promotion effects within companies and promotion effects including company changes. To this end, we specify an alternative measure of job promotions based on a narrow definition of upward moves in which only skill level increases within a firm are considered as a promotion (Zucco and Bächmann, 2020). We then run event study estimates using the narrow promotion measure as the outcome variable, and compare our findings to the previous estimates based on promotions including company changes. The resulting estimates are presented in Figure 4.5.



Notes: The plot shows event study estimates with 95 percent confidence intervals of an increase in the ETR on all promotions and on within-company promotions using ISCO-88 skill levels over time. The vertical red line indicates the time of the 2007 reform. Estimates based on employed individuals born between 1953-1964. Data Source: SOEP v36, 2000-2013.

Figure 4.5: Within-Company Promotion Effects

While coefficient estimates are sizeable and significant in the baseline scenario, estimates using the within-company promotion measure yield considerably smaller treatment effect estimates that are also less precisely estimated. One cautious interpretation of this finding is that the pooled promotion effects are largely attributable to proactive career orientation on the part of the employee, possibly resulting in intensified job switching, rather than reflecting employers' increased investment into the human capital of their current employees. Data on the stated reasons regarding the termination of a job contract among job switchers indicates that almost one third of all job terminations are initiated by the employee (Table D.6). Nonetheless, alternative linked employer-employee data could lend additional support to - or refute - the conjecture that employees' response to the NRA increase explains observed promotion effects.

4.5 Robustness Analyses

Section 4.5.1 discusses the findings from various extensions and sensitivity checks of the previous empirical specification. In Section 4.5.2, we test our hypotheses about the effects of working longer on career trajectories using an earlier reform of the German public pension system, the abolition of the 'pension for women' in 1999.

4.5.1 Sensitivity Checks

Effects without the 2007 Manufacturing Sector One concern with the previous analyses is that the post-reform period coincides with the Great Recession, which induced changes in labor markets that might differ across different age cohorts. For example, dismissal protection regulation in Germany favours older individuals as well as those with longer tenure, leading to age-specific variation in the termination of contracts for operational reasons (Kirchmann and Rosemann, 2010). To test if our results are robust to this concern, we estimate our baseline model as well as the event study regressions, excluding observations from the manufacturing sector, which is the industrial sector most heavily influenced by the Great Recession (Möller, 2010).[21] The results are presented in Section 4.4, and in Appendix D.2.7. We find similar patterns as in our main specification, with some reduced precision due to the reduced sample size, but given that the overall picture does not change, we are confident that the observed effects are not driven by the Great Recession.

Increasing the Time Horizon We investigate the sensitivity of our findings to the specification of the time horizon by estimating alternative regressions over a longer post-reform period. One caveat of extending the time horizon is that other reforms of the public pension system were enacted in 2014, and might independently affect career trajectories (see the discussion in Section 4.3.2). Assuming that the effects of the 2014 reform took at least some time to become manifest, we expand our analysis until 2015, and present the corresponding estimates in Appendix D.2.8. We find very similar effects for the promotion outcomes, both in terms of magnitude and significance. In contrast, the wage effects now become significant at the five percent confidence level, which might either reflect delayed causal effects of the reform, or changes in sample composition stemming from older individuals increasingly exiting the labor force.

Logistic Model We further validate our findings by estimating the models with binary dependent variables using logistic regressions. Figure D.10 presents first supportive evidence confirming significant reform effects on promotions based on univariate logistic regression: While future increases in the ETR are not correlated with the probability of promotion in the pre-reform period, the coefficient is positive and significant in the post-reform period. Table D.9 presents estimates from bivariate and multivariate logistic regressions, further validating the direction and overall magnitude of the reform effects. The relevant coefficient estimate from the multivariate model is positive and significant,

[21] In Germany, the Great Recession mostly influenced export-oriented sectors, particularly manufacturing, but the overall increase in unemployment was low (Möller, 2010; Kirchmann and Rosemann, 2010). Germany exhibited an overall upward trend in employment since 2005, and the Great Recession only led to a small dip in employment between 2008 and 2010 (see Figure D.1 in the Appendix).

confirming that an increase in the ETR significantly increases the odds of getting promoted (odds ratio = 1.768).

Sorting into Employment One concern with our empirical analyses are potential sorting effects. Previous studies show that pension reforms affect labor supply choices, potentially altering the composition of the labor force (Gohl, 2022; Carta and De Philippis, 2022). For instance, Gohl (2022) finds that employment effects of the 2007 pension reform are concentrated among individuals in low-physical-intensity and highly specialized service sector occupations. Hence, individuals employed in the post-reform period may represent a differently selected sample relative to the pre-reform population, which may in turn affect promotion and wage outcomes. To test if our results are affected by potential sorting effects, we repeat our main analysis conditioning on pre-reform employment. Specifically, we only include individuals who were employed either full-time or part-time in the year preceding the reform (2006). We find slightly smaller promotion effects (2-3.5 p.p.) that remain significant in some specifications but not in others, suggesting that some sorting effects may be at play (see Table D.10 in Appendix D.2.10). However, conditioning on pre-reform employment substantially reduces the sample size and, thus, statistical power. For this reason, we use an alternative approach using individual fixed effects below.

Individual Fixed Effects We fully utilize the longitudinal structure of the SOEP data and estimate our main regressions with individual fixed effects instead of cohort fixed effects. By using only within-individual variation in job levels for identification, including individual fixed effects, to a certain extent, also accounts for potential sorting similarly to conditioning on pre-treatment employment. The resulting coefficient estimates are presented in Appendix D.2.11. Promotion effects based on skill levels are almost identical to our main specification using cohort fixed effects, while estimates based on occupational job levels are slightly smaller, but overall the findings do not diverge systematically from our main results.

4.5.2 The 1999 Pension Reform

To further study the robustness and the external validity of our findings, we exploit a second reform of the German pension system and analyze if our results replicate in a different context. To this end, we revisit a well-studied pension reform which restricted the options for early retirement among German women (e.g. Barschkett et al., 2022; Geyer and Welteke, 2021; Gohl et al., 2021; Geyer et al., 2020; Fischer and Müller, 2020). The reform, implemented in 1999, abolished the so-called 'pension for women' for all birth cohorts from 1952 onwards. Women born up to and including 1951 were allowed to retire at age 60 under certain conditions. For all women born later, the reform raised the minimum retirement age to 63, which corresponds to a substantial and immediate extension of the expected working life by three full years. We utilize the variation in employment histories after the announcement of the reform in 1998 between the adjacent 1951 and 1952 birth cohorts to estimate the causal effects of a prolonged work horizon on job mobility and wage growth among women.

Data and Sample We use survey waves 1995 to 2006 of the German Socio-Economic Panel (SOEP), excluding later periods to avoid overlap with the 2007 pension reform.

Our sample consists of employed women of birth cohorts 1951 and 1952, who are aged between 43 and 55 years in the survey period. We employ similar sample conditions as in the main analyses, excluding individuals who are self-employed, civil servants, in training, or in the military, as well as observations with missing information in the key outcome variables.

Empirical Strategy We estimate the effects of the 1999 pension reform on promotion and wage outcomes using a similar Differences-in-Differences specification as in Section 4.3.1, except the treatment indicator is now binary. Specifically, we exploit the variation in career paths between women belonging to the 1951 cohort, who could still claim the pension for women and retire at age 60, and women born in 1952, who faced the same early retirement regulation as men from 1999 onwards, with a minimum retirement age of 63 years. The expected time to retirement (ETR) was hence shifted by three full years between the adjacent 1951 and 1952 cohorts.

The formal regression equation is given by

$$Y_{it} = \beta_0 + \beta_1 \mathbb{1}[\Delta ETR_c > 0] \times post1999_t + \alpha_t + \epsilon_{it} \tag{4.2}$$

where Y_{it} is the outcome variable of interest, $\mathbb{1}[\Delta ETR_c > 0]$ is the cohort-specific binary treatment variable indicating whether individuals faced a change in the expected retirement age between the post- and the pre-reform rule, i.e. $\mathbb{1}[ETR_{post1999} - ETR_{pre1999} > 0]$, and $post1999$ is a binary variable indicating the post reform period. The coefficient β_1 is the coefficient of interest capturing the impact of a three year increase in the expected retirement age after the introduction of the reform. We estimate bivariate specifications, as well as specifications with year fixed effects, α_t, to account for time trends and general macroeconomic developments.

Results Table 4.5 presents coefficient estimates of the 1999 reform on job promotion probabilities and wage growth based on DiD regressions. We present additional graphical evidence of the reform effects in Section D.2.13 in the Appendix. In comparison to the main empirical analyses, this robustness exercise is based on women only, and refers to a different observation period (1995-2006, rather than 2000-2007). Nonetheless, the results for the 1999 pension reform are strongly aligned with our main findings: We find an increase in the probability of getting promoted by 9.2 percentage points for a three year increase in the expected time to retirement within the first seven years after the reform. This corresponds to an increase of about 3.1 percentage points for a one-year increase in the ETR, over a period of seven years. We further confirm our previous findings indicating small but insignificant effects of extending the work horizon on hourly wage growth. At least within the first seven years after raising the retirement age, increases in job mobility do not involve significant changes in hourly wage profiles. Hence, in analyzing the effects of working longer on career advancement, we document similar patterns exploiting two different reforms of the German pension system for identification.

Table 4.5: Estimation Results for the 1999 Pension Reform

	Job Promotions		Hourly Wage Growth	
	(1)	(2)	(3)	(4)
Increase in ETR × 1999-2006	0.0928**	0.0921**	0.0188	0.0205
	(0.0399)	(0.0398)	(0.0175)	(0.0175)
Observations	748	748	1,679	1,679
Time FE	N	Y	N	Y

Notes: SOEP v36 (1995-2006). Differences-in-Differences estimates of the reform effects for employed women among cohorts born between 1951 and 1952. Job promotions are measured based on changes in the ISCO skill level. Hourly wage growth is measured in percent. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01. ETR = Expected time to retirement.

4.6 Conclusion

This paper studies the effects of raising the statutory retirement age on career advancement and wage dynamics among individuals who are still relatively far from retirement. Increasing the normal retirement age can lead to behavioral adjustments among younger workers who face an increase in the expected work horizon and may subsequently alter their labor market choices.

We utilize quasi-exogenous variation in the expected duration of the working life induced by changes in pension eligibility rules in Germany to provide novel causal evidence of changes in employment trajectories among workers facing career extensions. Specifically, we detect sizeable effects of a prolonged work horizon on occupational mobility. A one year increase in the expected time to retirement increases the probability of reaching a higher-ranked position by between 2.8 to 5.9 percentage points within the first six years after the increase in retirement age was announced. Despite revealing sizeable effects on promotion rates, our empirical analyses show no corresponding changes in wage dynamics. Thus, further training and professional advancement do not guarantee improvements in remuneration. Consistent with previous work, employers seem to respond to longer careers at non-pecuniary margins, such as by promoting career advancement and training (Gohl et al., 2021; Brunello and Comi, 2015), or by delaying hiring (Ferrari et al., 2022). Future research may investigate the obstacles inhibiting a stronger link between job promotions and wage dynamics. Potentially, a fundamental change in pay and promotion practices over the life course needs more time for behavioral adjustments to take hold and for social norms regarding the typical working career to change.

Chapter 5

Expectation Management of Policy Leaders: Evidence from COVID-19

It is published as Haan, P., Peichl, A., Schrenker, A., Weizsäcker, G., & Winter, J. (2022). Expectation management of policy leaders: Evidence from COVID-19. Journal of Public Economics, 209, 104659. DOI: https://doi.org/10.1016/j.jpubeco.2022.104659

Appendices

Appendix A

Appendix to Chapter 1

A.1 Data

A.1.1 Survey Instrument

Below is a description of the survey instrument used to elicit expectations of full-time workers about counterfactual earnings in part-time. Part-time workers are asked to consider the opposite scenario of switching to a full-time position of 40 hours per week.

Please imagine you were to switch to a part-time job from now on working 20 hours per week. Please only consider part-time jobs that you could carry out with your qualification.

(a) What monthly gross income do you expect to earn when working part-time at 20 hours per week?
(b) How likely do you think it is that a part-time position at 20 hours per week yields a gross income of less than X-20% per month?*
(c) How likely do you think it is that a part-time position at 20 hours per week yields a gross income of more than X+20% per month?*

**Please report your answer in percent. 0% means 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 (a)]

A.1.2 Survey Administration

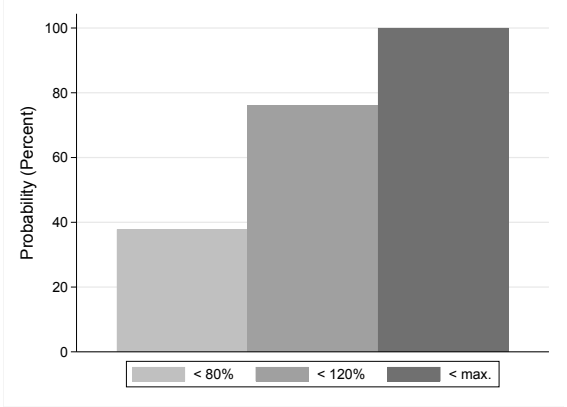
Sample design and field work of the SOEP and the SOEP Innovation Sample (SOEP-IS) are almost identical. For both surveys, participating households were initially selected through multi-stage random sampling with regional clustering. Face-to-face interviews take place once a year and last approximately 1.5-2 hours. Participants receive small gifts upon completion of each interview, as well as small cash incentives. Households either receive 5 Euros per completed personal interview and 10 Euros per household interview, or they receive a lottery ticket for the charitable TV lottery "Ein Platz an

der Sonne" (A place in the sun). Administration of both surveys lies with the German Institute for Economic Research, DIW Berlin, but Kantar Public (formerly TNS Infratest) is responsible for the field work, including software programming, interviewer recruitment, interviewer training, and coordination of interviews.

A.2 Probabilistic Analysis

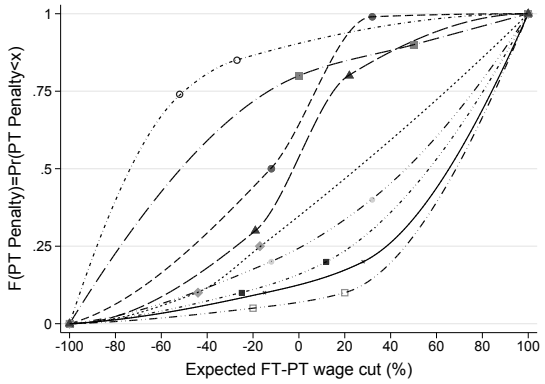
A.2.1 Subjective Probability Distributions

In addition to providing point estimates of the expected counterfactual hourly wage in Euros, respondents in Wave 2016 of the SOEP-IS report the subjective probability for earning less than 80 percent and more than 120 percent of their numeric point estimate (see Section A.1.1 for the question wording). Figure A.1 illustrates the average discrete subjective CDF. I use non-parametric spline interpolation to fit individual-specific smooth subjective CDFs, following Engelberg et al. (2009). Non-parametric techniques allow for flexible approximations to individuals' subjective distributions and have been shown to outperform parametric approximations (Bellemare et al., 2012). The fitted CDFs pass through reported point estimates, as well as through the respective wage thresholds associated with 80 percent and 120 percent of individual-specific point estimates.



Notes: Mean discrete subjective cumulative density function (CDF) for expected wages based on reported subjective probabilities. SOEP-IS (2016).

Figure A.1: Discrete Subjective CDF



Notes: Fitted smooth subjective CDFs for selected individuals, based on subjective probabilities and non-parametric piecewise cubic hermite interpolating polynomials. SOEP-IS (2016).

Figure A.2: Fitted Smooth Subjective CDFs

I use monotonicity preserving piecewise cubic Hermite interpolating polynomials based on Matlab's PCHIP, using a grid step size of one percent and setting the lower and upper bounds to -100 percent and 100 percent, respectively. Individuals who report incomplete or implausible probabilities (i.e. summing to more than 100 percent) are excluded from the probabilistic analyses. Figure A.2 illustrates the interpolation for ten randomly selected individuals. From the fitted distributions, I derive alternative measures of central tendency (subjective means and medians) and construct subjective standard deviations, interquartile ranges (P75-P25) and point prediction percentiles to measure belief uncertainty, as pioneered by Engelberg et al. (2009).

A.3 Discrete Choice Model

A.3.1 Tax and Welfare Regime

The model implements details of the 2005 German tax and benefit system based on features of the German Tax and Benefit Microsimulation Model (STSM) described in Steiner et al. (2012) to simulate net income for each employment choice, following three steps: First, I subtract professional and deductible expenses to derive taxable income. Second, I calculate income tax liability by applying tax formulas depending on marital status. Finally, I deduct liabilities from gross income and add transfers to obtain net income.

To obtain taxable income in step one, gross labor income of the household is converted into real terms (base year 2005) and aggregated to annual amounts. For counterfactual choice categories, I derive alternative-specific gross earnings by multiplying hours times the hourly wage rate that is allowed to vary across full-time and part-time choices. I disregard income components from alternative sources such as capital income or income from renting and leasing.[1] Given gross annual real income, I deduct the lump-sum amount of 920 Euros for professional expenses ("Werbungskosten") for all workers. In addition, actual or lump-sum deductible expenses ("Sonderausgaben") are subtracted up to a maximum amount. I simplify this step and consider only the general flat rate amount of 36 Euros ("Pauschbetrag") as well as expenses for social security contributions.[2] Table A.1 presents detailed information on how deductible expenses are accounted for. For simplicity, the model does not incorporate loss deductions and extraordinary deductible expenses ("aussergewöhnliche Belastungen"). One further simplification I resume to involves the distinction between child allowances that are deducted before applying the tax function and child benefits ("Kindergeld"), which are added afterwards. A more accurate account of the tax-benefit system would conduct a higher-yield test ("Günstigerprüfung") and assign the more favorable rule (Steiner and Wrohlich, 2008). I abstract from this distinction and assume all couples with children receive child benefits.

Table A.1: Annual Deductable Expenses for Social Security Contributions in 2005

	Single individual	Married couple
Minimum ("Vorsorgepauschale")	$0.2 \cdot RV \ + \ min(0.12 \cdot INC, 1900)$	$0.2 \cdot RV_{HH} \ + \ min(0.12 \cdot INC_{HH}, 3800)$
Actual expenses		
Bracket 1 ("Diff. Vorwegabzug")	$max(0, 3068 - 0.16 \cdot INC)$	$max(0, 6136 - 0.16 \cdot INC_{HH})$
Bracket 2	$min(1334, SV - Bracket\ 1)$	$min(2668, SV - Bracket\ 1)$
Bracket 3	$min(667, SV - Bracket\ 1 - Bracket\ 2)$	$min(1334, SV - Bracket\ 1 - Bracket\ 2)$
Maximum	2001	4002

Notes: All amounts in Euros and annual terms. RV= old age pension contributions ("Rentenversicherung"). HH= household level. INC= gross income. SV= total social security contributions ("Sozialversicherung"). Old age (RV) contributions deductable up to a correction factor (20% in 2005)

Given taxable income, I obtain income tax liability of the household in step two. In Germany, due to the joint taxation of married couples ("Ehegattensplitting"), singles and married individuals are taxed differently. For singles, income tax formulas are applied

[1] Since I exclude pensioners and self-employed women, I also disregard income from pensions or self-employment.

[2] I abstract from other deductible expenses such as insurance contributions, alimony payments, church tax, expenses for training, donations, and tax consultancy expenses

directly to individual taxable income. For married couples, total taxable income of the household is first divided by two. Income tax formulas are then applied to half the amount of total taxable household income. The derived tax liability is then doubled to determine overall tax liability of the couple. Table A.2 contains income tax formulas as well as minimal and maximal marginal tax rates for all available tax brackets. Income is not taxed below an annual allowance of 7,664 Euros and tax rates evolve according to a partially linear rule until a top income threshold of 52,152 Euros, after which income is taxed at a constant marginal rate of 42%.

Table A.2: Income Tax Formula in 2005 (§ 32 a Abs. 1 EStG)

Zone	Tax bracket	Tax formula	MTR (min)	MTR (max)
1	≤ 7664	t=0	0	0
2	7665-12739	t=(883.74Y + 1500)Y	15%	23.97%
3	12740-52151	t=(228.74Z + 2397)Z + 989	23.97%	42%
4	≥ 52152	t=0.42X - 7914	42%	42%

Notes: Income and tax liabilities refer to annual Euro amounts. MTR = marginal tax rate. Y and Z are 1/10000 of excess income over upper bound of the previous bracket. X is taxable income.

In step three, I compute net income by deducting income tax, social security contributions, and the solidarity surcharge ("Solidaritätszuschlag")[3] from gross income and by adding transfers and benefits. I calculate unemployment benefits according to ALG II standard rates ("Regelbedarfssätze") that differ between East and West German regions and by household composition (Table A.3). Payments are means-tested and individuals are only eligible for unemployment transfers if joint household income, including spousal income, is lower than transfer claims and if household assets are below exempted wealth allowances. I simplify the means-test by assuming households are ineligible for social assistance as soon as one spouse has positive labor income. In accordance with the STSM, I do not model payments from unemployment insurance (ALG I).[4] Child benefits are added once for each couple (the first three children receive 154 Euros each, all additional children receive 179 Euros each). I refrain from covering any additional benefits (e.g. allowances for housing, education, widows etc.).

Table A.3: Unemployment Benefit Standard Rates in 2005 (SGB II/Hartz IV and SGB XII)

	Single adults (I)	Adults in couples (II)	Youth 14 - 18 (III)	Children < 14 (IV)
East	331	298	265	199
West	345	311	276	207

Notes: Monthly allowances per person in Euros.

[3]Solidarity surcharge of 5.5% on tax liability accrues for couples (individuals) owing above 1944 (972) Euros annual tax.

[4]Individuals who worked in the previous year are, in principle, entitled to payments from unemployment insurance for the first 6 months after becoming unemployed. These payments are not means-tested and replace 60-67% of previous net income. I follow the STSM and assume all unemployed directly apply for unemployment benefits (ALG II).

A.3.2 Simulated Log Likelihood Function

If full-time and part-time wages were observed for all individuals, including non-workers, the log-likelihood function would be given by

$$ln(L(\theta)) = \sum^{N} ln\left(\frac{exp(\beta' x_{ni})}{\sum_j exp(\beta' x_{nj})}\right) + \sum^{N}\left\{ln\ \phi\left(\frac{lnw_n - Z_n'\gamma}{\sigma_w}\right) - ln\ \sigma_w\right\} \quad (A.1)$$

where the first summand denotes the likelihood contributions from logit choice probabilities over hours choices and the second term gives the likelihood of the wage equation residuals, assuming log-normality, where $\phi(.)$ is the normal density.

Accounting for unobserved wage offers, two types of prediction errors must be integrated out, resulting in the following simulated log-likelihood function:

$$\begin{aligned}
ln(SL) = &\sum^{FT} ln\left\{\frac{1}{R}\sum^{R} P_{n,FT}^{(r)}\right\} + \sum^{FT}\left\{ln\ \phi\left(\frac{lnw_n^{FT} - Z_n'\gamma^{FT}}{\sigma_w^{FT}}\right) - ln\ \sigma_w^{FT}\right\} \\
&+ \sum^{FT}\left\{ln\ \frac{1}{R}\sum^{R}\phi\left(\frac{lnw_n^{PT,(r)} - Z_n'\gamma^{PT}}{\sigma_w^{PT}}\right) - ln\ \sigma_w^{PT}\right\} \\
&+ \sum^{PT} ln\left\{\frac{1}{R}\sum^{R} P_{n,PT}^{(r)}\right\} + \sum^{PT}\left\{ln\ \phi\left(\frac{lnw_n^{PT} - Z_n'\gamma^{PT}}{\sigma_w^{PT}}\right) - ln\ \sigma_w^{PT}\right\} \\
&+ \sum^{PT}\left\{ln\ \frac{1}{R}\sum^{R}\phi\left(\frac{lnw_n^{FT,(r)} - Z_n'\gamma^{FT}}{\sigma_w^{FT}}\right) - ln\ \sigma_w^{FT}\right\} \\
&+ \sum^{OLF} ln\left\{\frac{1}{R}\sum^{R} P_{n,OLF}^{(r)}\right\} + \sum^{OLF}\left\{ln\ \frac{1}{R}\sum^{R}\phi\left(\frac{lnw_n^{FT,(r)} - Z_n'\gamma^{FT}}{\sigma_w^{FT}}\right) - ln\ \sigma_w^{FT}\right\} \\
&+ \sum^{OLF}\left\{ln\ \frac{1}{R}\sum^{R}\phi\left(\frac{lnw_n^{PT,(r)} - Z_n'\gamma^{PT}}{\sigma_w^{PT}}\right) - ln\ \sigma_w^{PT}\right\}
\end{aligned} \quad (A.2)$$

where $P_{n,i}^{(r)} = \frac{exp(\beta' x_{ni})}{\sum_j exp(\beta' x_{nj}^{(r)})}$ denotes the simulated logit choice probability from draw $r \in R$. $w_n^{FT,(r)}$ and $w_n^{PT,(r)} \in x_{nj}^{(r)}$ are simulated full-time and part-time wage offers.

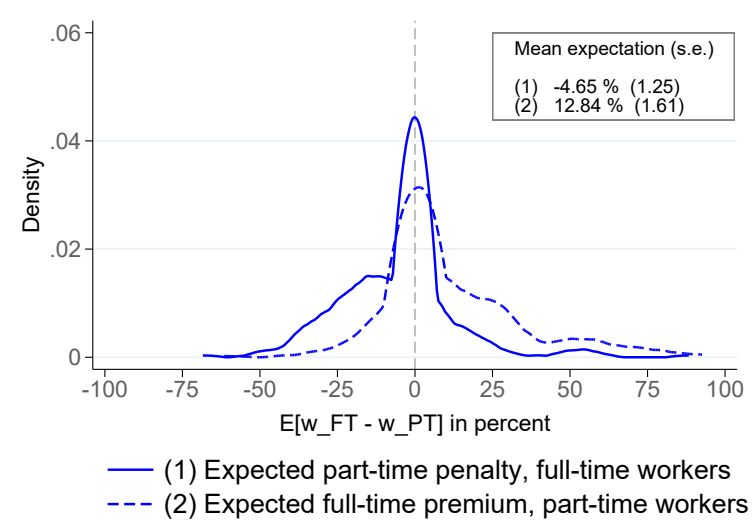
A full information maximum simulated likelihood estimator is given by

$$\hat{\theta}_{FIMSL} = argmax_\theta\ ln(SL), \qquad \theta = (\beta, \gamma, \sigma_w^{FT}, \sigma_w^{PT})$$

A.4 Additional Results

A.4.1 Perceived Returns based on Working Hours including Overtime

In this section, I explore the implications of including current overtime in defining women's working hours for estimating the perceived returns (also see the discussion in Section 1.3.1). The asymmetry in beliefs between full-time workers and part-time workers documented in Figure 1.1 is amplified further when expectations take into account current overtime (Figure A.3). Full-time working women expect even smaller part-time wage penalties when overtime is taken into account (yielding small expected part-time wage premiums, -4.65 percent), whereas part-time working women expect even stronger full-time premiums (12.84 percent). This finding is not surprising, given that an inclusion of overtime hours reduces the current factual hourly wages of both full-time workers and part-time workers, while leaving untouched perceived counterfactual wage offers. Hence, perceived pay gaps between working full-time and part-time decrease for full-time workers and increase for part-time workers.



Notes: The plot shows the distribution of the expected part-time wage penalty amongst full-time workers (1, solid line, N = 312) and the expected full-time wage premium amongst part-time workers (2, dashed line, N = 349). Working hours are defined as actual hours including overtime. The box shows sample means with standard errors (s.e.) in parentheses. SOEP-IS (2016-19).

Figure A.3: Distribution of the Perceived Returns based on Hours Including Overtime

A.4.2 Perceived Returns by Occupation and Industry

Here I show how expectations covary with current occupation and industry.

Table A.4: Estimates of the Perceived Returns by Occupation and Industry

	Full-time workers		Part-time workers	
	Mean	S.E.	Mean	S.E.
All women	0.21	(1.27)	6.70	(1.56)
International Standard Classification of Occupations (ISCO 2008)				
1. Managers	6.69	(4.85)	4.97	(6.96)
2. Professionals	3.72	(4.99)	11.20	(4.65)
3. Technicians and associate professionals	−1.09	(1.67)	5.09	(1.97)
4. Clerical support workers	−0.77	(1.76)	5.77	(4.12)
5. Service and sales workers	1.25	(3.60)	9.58	(4.52)
7. Craft and related trades workers	−16.73	(6.78)	−5.78	(21.49)
8. Plant and machine operators, assemblers	3.99	(3.04)	43.89	(28.19)
9. Elementary occupations	−3.52	(5.27)	−1.07	(2.92)
German Classification of Occupations (KldB 2010)				
1. Agriculture, Forestry, Farming, Gardening	−6.33	(3.61)	3.20	(6.50)
2. Raw Materials, Goods, Manufacturing	−2.25	(8.93)	18.76	(15.90)
3. Construction, Architecture, Technical Building	−4.03	(3.10)	−2.51	(4.11)
4. Natural Sciences, Geography, Informatics	0.03	(0.05)	2.64	(4.76)
5. Traffic, Logistics, Safety, Security	−0.26	(2.53)	−0.23	(3.63)
6. Commercial Services, Trading, Tourism etc.	0.06	(2.89)	7.52	(4.49)
7. Business Organization, Accounting, Law etc.	−1.64	(1.29)	6.53	(2.90)
8. Health Care, Social Sector, Teaching etc.	4.44	(3.14)	8.05	(2.49)
9. Philology, Literature, Humanities etc.	−5.95	(6.12)	−1.03	(2.37)

Notes: SOEP-IS 2016-19. The Table shows sample means of the expected part-time wage penalty among full-time workers, $\bar{E}[\omega_{FT} - \omega_{PT}|FT]$, and the expected full-time premium among part-time workers, $\bar{E}[\omega_{FT} - \omega_{PT}|PT]$ (in percent), with standard errors (S.E.) clustered at the person-level in parentheses. Results based on self-reported part-time status and contractually agreed working hours.

A.4.3 Perceived Returns by Experience in the Other Sector

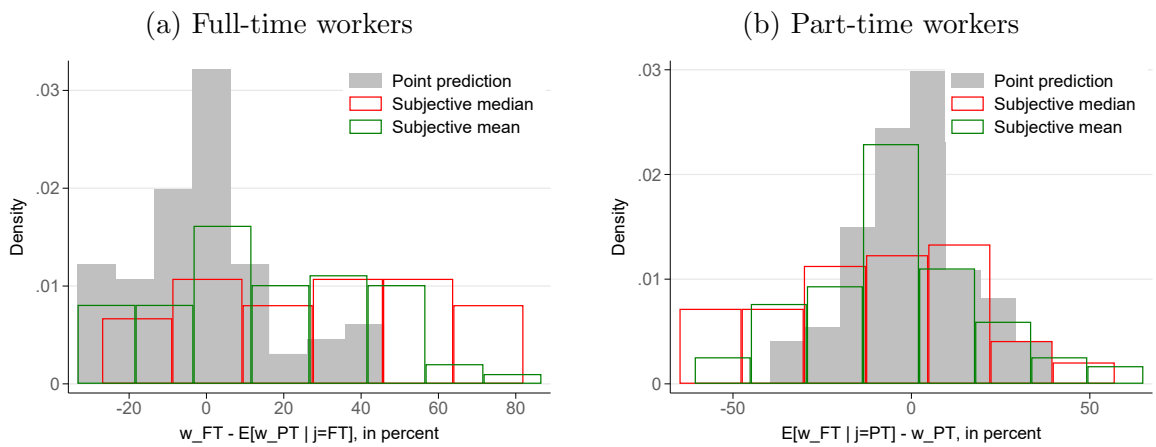
To investigate if there are learning effects, Table A.5 shows how perceived returns covary with work experience in the other sector. I do not observe the full employment trajectories of respondents in the SOEP-IS. To proxy work experience in the other sector, I restrict the sample to workers observed in Wave 2019 of SOEP-IS sample I5 for which I have complete information on past employment status from 2016 onwards (N=70). I then distinguish part-time workers who were observed in part-time employment for the past 3 years from part-time workers who were observed to work full-time at least once since 2016. Likewise, I distinguish full-time-only workers from full-time workers with experience in part-time employment. Given these (limited) proxies of work experience, I do not find any evidence of learning effects, but more research with better measures and larger samples would be incredibly useful.

Table A.5: Estimates of the Perceived Returns by Experience in the Other Sector

	Mean	(S.E.)
A. Full-time workers		
Full-time only	−1.34	(1.34)
Ever part-time in last 3y.	−1.11	(1.11)
Δ Mean Diff.	−0.23	(1.73)
B. Part-time workers		
Part-time only	5.29	(2.56)
Ever full-time in last 3y.	5.80	(2.85)
Δ Mean Diff.	−0.51	(3.82)

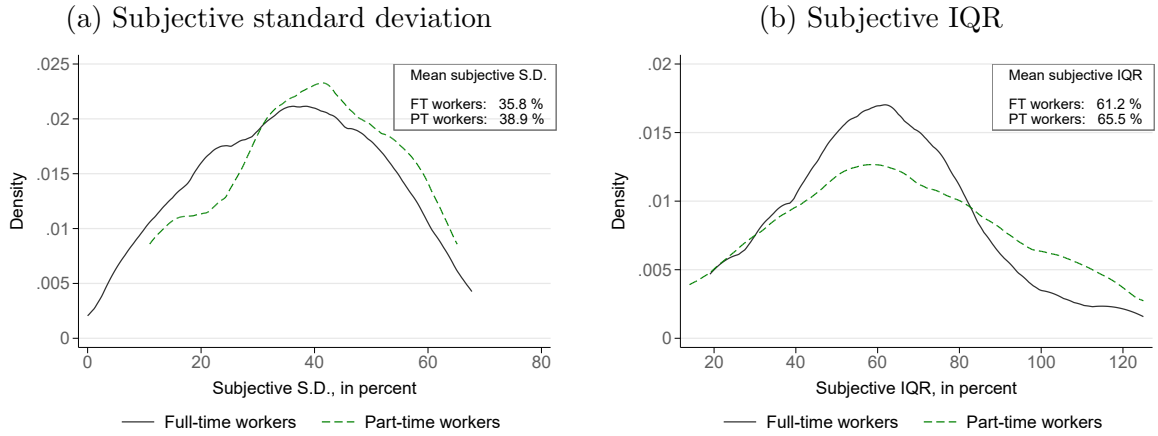
Notes: SOEP-IS (I5) 2019. The Table shows sample means of the expected part-time wage penalty among full-time workers (Panel A, N=33), and the expected full-time premium among part-time workers (Panel B, N=37), separately by work experience in the other sector. Robust standard errors (S.E.) in parentheses. All values in percent.

A.4.4 Belief Uncertainty and Subjective Central Tendency



Notes: The plots compare reported point predictions of the perceived returns with measures of central tendency obtained from subjective probabilities. N=66 (Panel a), N=75 (Panel b). SOEP-IS (2016).

Figure A.4: Alternative Measures of Central Tendency



Notes: The plots show kernel density estimates of the fitted subjective standard deviation (Panel a) and the subjective interquartile range, the IQR, (Panel b), based on subjective bin probabilities, separately for full-time workers (solid black line, N=66) and part-time workers (dashed green line, N=75). The IQR is given by the difference between the 75th and the 25th percentile of the fitted distribution. SOEP-IS (2016).

Figure A.5: Alternative Measures of Belief Uncertainty

Table A.6: Uncertainty and Subjective Central Tendency

	Full-time workers		Part-time workers	
Subjective central tendency (CT)	Mean	Median	Mean	Median
S.D. < P25	8.2	5.5	2.4	−4.1
S.D. P25-P50	12.2	20.8	−5.3	−9.8
S.D. P50-P75	16.8	19.3	−7.7	−10.1
S.D. > P75	27.0	41.5	−7.6	−13.1
Corr (CT, S.D.)	0.52	1.46***	−0.08	−0.01
Corr (DIST, S.D.)	0.40*	0.91**	0.50***	0.80***

Notes: SOEP-IS 2016. The Table shows sample averages of the fitted subjective means and medians in percent by respondent uncertainty (measured by different percentiles of the subjective standard deviation, S.D.) for full-time workers (N=66) and part-time workers (N=75). Correlations of subjective central tendency (CT) and standard deviations, as well as of the absolute distance between reported point estimates and subjective central tendency (DIST), are adjusted for worker education, children, age, marital status, region, immigrant background, overtime hours, managerial responsibility, sector (public/private), firm size, tenure and contract type (permanent/fixed-term). Estimation with robust standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Correlates of Belief Uncertainty

	Full-time workers		Part-time workers	
Dep.Var. = Subjective S.D.	Coef.	Std.Err.	Coef.	Std.Err.
Education: Basic	10.13	(1.56)	1.04	(0.17)
Education: Tertiary	−13.11*	(−1.94)	−4.38	(−0.63)
With children	−14.79**	(−2.66)	−2.86	(−0.54)
Age > 40y.	−8.71*	(−1.98)	2.14	(0.41)
Married	6.04	(1.06)	−7.22	(−0.78)
Eastern Germany	17.87***	(3.56)	1.37	(0.28)
Native born	−10.70	(−1.33)	4.03	(0.92)
Overtime hrs. > 0	9.78**	(2.09)	−2.00	(−0.45)
Manager	18.84***	(3.25)	13.28	(1.21)
Public sector	9.34*	(1.71)	−9.12**	(−2.28)
Firm size > 200	−6.34	(−1.58)	−2.59	(−0.61)
Fixed term contract	−3.86	(−0.83)	−0.72	(−0.10)
Tenure > 10y.	2.99	(0.64)	−2.47	(−0.60)

Notes: SOEP-IS 2016. The Table shows OLS estimates of belief uncertainty, measured by the fitted subjective standard deviation obtained from bin probabilities, on worker and job characteristics. N=51 (full-time workers), N=68 (part-time workers). Estimation with a constant and robust standard errors (Std.Err.) in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4.5 Reduced Form Estimation of the Observed Returns

In this Appendix, I present alternative ('reduced-form') estimates of the part-time wage penalties and premiums. Section A.4.5 presents results from OLS and fixed effects estimation of sector-specific log wage functions. Section A.4.5 shows wage changes for women who actually switched between full- and part-time employment and discusses the identification challenges associated with this approach.

Reduced Form Wage Estimation of Sector-specific Wage Functions

I estimate sector-specific log wage equations for full-time and part-time work to impute counterfactual full-time wages for all part-time workers and vice versa, holding fixed individual-specific characteristics (endowments). A part-time wage penalty or premium can unfold if parameters vary across sectors such that the returns to identical characteristics differ between part-time and full-time work; for instance, if the returns to work experience or to having a permanent contract differ across employment states.

Formally, sector-specific log wage equations for full-time and part-time work are given by

$$ln(w_{jn}) = \alpha_j + Z_n'\gamma_j + \mu_{jn} + \epsilon_{jn} \tag{A.3}$$

where parameters and disturbances may vary over $j_n \in \{FT, PT\}$. The vector Z_n collects basic controls for years of education, a quadratic in part-time and full-time work experience (in years), as well as binary indicators for region (East/West) and immigrant background; if specified broadly Z_n additionally contains occupation major group (1-digit ISCO-88), industry (2-digit NACE), linear and quadratic tenure, as well as binary indicators for firm size (> 200), public sector, and fixed term contract. An individual-specific fixed effect that may vary over j is given by μ_{jn}.

Table A.8 presents the reduced-form estimates of Equation (A.3). Point estimates vary widely across different specifications, but largely confirm previous findings by Hirsch (2005) who documents stronger wage effects for full-time workers switching to part-time relative to the wage effects for part-time workers switching to full-time.

Table A.8: Reduced Form Estimates of the Observed Returns

	(1)		(2)		(3)		(4)	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
1. OLS, basic controls								
PT Penalty FT Workers	8.56	(0.21)***	9.16	(0.20)***	5.26	(0.16)***	4.15	(0.14)***
FT Premium PT Workers	−0.21	(0.13)	0.45	(0.13)***	−0.72	(0.12)***	−0.99	(0.13)***
2. OLS, broad controls								
PT Penalty FT Workers	3.16	(0.16)***	3.89	(0.15)***	−0.49	(0.16)**	−1.96	(0.12)***
FT Premium PT Workers	−2.20	(0.14)***	−1.14	(0.12)***	−4.52	(0.15)***	−4.72	(0.14)***
3. Fixed effects, basic controls								
PT Penalty FT Workers	11.39	(0.31)***	12.57	(0.32)***	7.35	(0.24)***	7.46	(0.21)***
FT Premium PT Workers	5.23	(0.27)***	5.80	(0.24)***	2.06	(0.23)***	2.99	(0.23)***
4. Fixed effects, broad controls								
PT Penalty FT Workers	8.71	(0.31)***	10.10	(0.31)***	6.95	(0.26)***	6.57	(0.24)***
FT Premium PT Workers	3.18	(0.29)***	4.03	(0.26)***	1.17	(0.25)***	1.31	(0.25)***
Part-time status	self-reported		self-reported		hours < 30		hours < 30	
Working hours	agreed hrs.		incl. overtime		agreed hrs.		incl. overtime	

Notes: The Table shows reduced form predictions of the part-time wage penalty for full-time workers and of the full-time wage premium for part-time workers, obtained after separate full- and part-time log wage regressions. All wage regressions are based on SOEP waves 2005-2016, with a minimum sample size of N=48,603. Predictions are presented for working women in full-time or in part-time employment sampled in GSOEP-Core 2016. Basic controls include years of education, linear and quadratic work experience in part-time and full-time, region (Eastern/ Western GER) and immigrant background. Broad controls add occupation major group (ISCO 88, 1 digit), industry (NACE,2 digit), linear and quadratic tenure and indicators for firm size > 200, public sector and fixed term contract. Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Identification based on Switchers

This section presents estimates of the average wage changes among women who actually switched from full-time to part-time employment ('full-time leavers') or from part- to full-time employment ('part-time leavers').

Formally, for $j \in \{FT, PT\}$, Mincerian log wage functions are given by

$$ln(w_{n,t}) = \alpha + \beta \cdot \mathbb{1}(j_{n,t} = j | j_{n,t-\eta} \neq j) + Z'_{n,t}\gamma + \mu_n + \epsilon_{n,t} \tag{A.4}$$

where for $j = PT$, $\mathbb{1}(j_{n,t} = PT | j_{n,t-\eta} = FT)$ indicates whether individual n switched from full- to part-time employment between time t and $t - \eta$ and for $j = FT$, $\mathbb{1}(j_{n,t} = FT | j_{n,t-\eta} = PT)$ indicates a respective transition from part- to full-time employment. The parameter of interest is given by β, measured conditional on the same vector of exogenous covariates described in Equation (A.3), $Z_{n,t}$, and an individual-specific fixed effect, μ_n. Table A.9 presents estimates of Equation (A.4) based on direct year-to-year transitions, $\eta = 1$, or from all transitions within the observation period 2005-2016, $\eta \in (1, 11)$.

Table A.9: Estimates of the Observed Returns based on Switchers

	(1)		(2)		(3)		(4)	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
1. OLS, direct transition								
PT Penalty FT Leavers	−1.87	(1.11)	0.07	(1.13)	−4.93	(1.30)***	−7.38	(1.09)***
FT Premium PT Leavers	−2.66	(0.90)**	−1.95	(0.92)*	−10.94	(0.96)***	−12.10	(0.91)***
2. Fixed effects, direct transition								
PT Penalty FT Leavers	−3.48	(1.10)**	−1.57	(1.14)	−11.92	(1.28)***	−12.20	(1.07)***
FT Premium PT Leavers	−3.47	(0.93)***	−1.37	(0.97)	−11.19	(1.09)***	−12.03	(0.99)***
3. OLS, any transition								
PT Penalty FT Leavers	3.43	(0.92)***	4.32	(0.93)***	0.42	(0.96)	−0.06	(1.03)
FT Premium PT Leavers	−1.63	(1.65)	−0.49	(1.66)	−6.57	(1.64)***	−7.16	(1.66)***
4. Fixed effects, any transition								
PT Penalty FT Leavers	−2.93	(1.26)*	−1.19	(1.30)	−8.88	(1.49)***	−0.06	(1.81)***
FT Premium PT Leavers	0.61	(3.20)	6.14	(3.20)	−5.41	(3.21)	−7.95	(2.47)**
Part-time status	self-reported		self-reported		hours < 30		hours < 30	
Working hours	agreed hrs.		incl. overtime		agreed hrs.		incl. overtime	

Notes: The Table shows reduced form estimates of the part-time wage penalty for full-time working women who switched to part-time (FT Leavers) and of the full-time wage premium for part-time working women who switched to full-time (PT Leavers) in percent, in comparison to stayers. Coefficient estimates are either based on women with direct year-to-year transitions between full- and part-time sectors (Models 1-2), or on women with at least one transition in the observation period (Models 3-4). Controls include years of education, linear and quadratic work experience in part-time and full-time, region (Eastern/ Western GER), immigrant background, occupation major group (ISCO 88, 1 digit), industry (NACE,2 digit), linear and quadratic tenure and indicators for firm size > 200, public sector and fixed term contract. All wage regressions are based on GSOEP-Core waves 2005-2016, OLS estimates contain additional survey year controls. Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Estimates of the observed returns to full- and part-time work based on women switching employment status differ notably from reduced-form and structural discrete choice estimates. Estimates based on within-variation generally yield no wage penalty for full-time workers switching to part-time; if anything, these estimates suggest small wage gains in part-time. Estimates for part-time leaving women further suggest wage losses in full-time.

To the extent that the subset of switchers differs from the population of interest, results based on switchers diverge from average treatment effects.

Table A.10: Composition of Switchers and Stayers

	FT Leaver	FT Stayer	Δ FT Leaver vs. Stayer (*p-val*)	PT Leaver	PT Stayer	Δ PT Leaver vs. Stayer (*p-val*)
Gross hourly wage (in Euros)	14.97	15.91	0.02	13.97	14.47	0.09
Agreed weekly hrs.	28.31	38.67	0.00	34.77	24.00	0.00
Overtime hrs. per week	3.15	3.27	0.66	2.86	2.20	0.00
Education (in years)	12.45	12.69	0.07	12.46	12.12	0.00
Age (in years)	44.85	42.78	0.00	43.53	47.06	0.00
With children (in percent)	0.29	0.14	0.00	0.35	0.45	0.00
Eastern Germany (in percent)	0.25	0.22	0.25	0.24	0.17	0.00
Native born (in percent)	0.77	0.83	0.02	0.77	0.81	0.11
Public sector (in percent)	0.34	0.29	0.04	0.31	0.33	0.45
Firm size > 200 (in percent)	0.48	0.53	0.08	0.47	0.45	0.36
Fixed term contract (in percent)	0.13	0.06	0.00	0.17	0.08	0.00
Tenure (in years)	11.04	12.11	0.07	9.73	12.21	0.00
Manager (in percent)	0.01	0.02	0.05	0.02	0.01	0.10
N	1,164	16,298		1,432	14,902	

Notes: Sample averages with population weights. Switchers defined based on direct year-to-year transitions between full- and part-time sectors. GSOEP-Core (2005-2016).

Table A.10 presents summary statistics for the subset of women who switched between full- and part-time ('Leavers'), comparing them to women who maintained their employment status ('Stayers'). Full-time leavers significantly differ from full-time stayers in a number of observable characteristics. Likewise, part-time leavers differ notably from part-time stayers. If leavers constitute a selected group, estimates of observed penalties and premiums from actual transitions are not transferable to the sample of stayers. Given that I elicit expectations about the part-time penalty (full-time premium) among a representative sample of full-time (part-time) working women, observed returns must be computed for the population of interest comprising both switchers and stayers. Therefore, I use the wage imputation technique in the main specification, further modeling the choice to work full- or part-time within a discrete choice framework.

A.4.6 FIMSL Estimation Results

Table A.11 presents the full set of estimation results of the discrete choice model for different specifications of part-time status and working hours.

Table A.11: FIMSL Estimation Results of the Discrete Choice Model

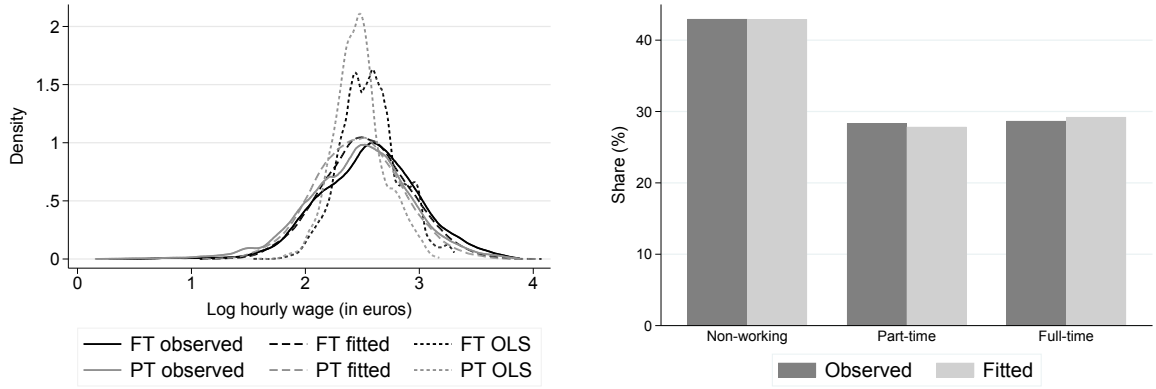
PT status: self-reported	**(1) Agreed hours**				**(2) Incl. overtime**			
	Full-time		Part-time		Full-time		Part-time	
Log wages	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Education (years)	0.091	0.001	0.090	0.001	0.091	0.001	0.087	0.001
FT experience (years)	0.030	0.001	0.028	0.001	0.034	0.001	0.030	0.001
FT experience sq.	0.000	0.000	−0.001	0.000	−0.001	0.000	−0.001	0.000
PT experience (years)	0.000	0.001	0.018	0.001	−0.003	0.001	0.016	0.001
PT experience sq.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
East	−0.282	0.003	−0.261	0.004	−0.287	0.004	−0.267	0.004
Foreign born	−0.061	0.004	−0.050	0.004	−0.066	0.004	−0.052	0.004
Constant	1.140	0.009	1.060	0.010	0.994	0.011	1.018	0.012
Std.Dev.	0.076	0.001	0.090	0.001	0.087	0.001	0.102	0.001
Hours choice		Coef.	Std.Err.			Coef.	Std.Err.	
Consumption		0.124	0.003			0.138	0.003	
Hours		0.038	0.001			0.036	0.001	
Hours × Kids		0.041	0.001			0.039	0.001	
Hours × East		−0.018	0.001			−0.017	0.001	
Log likelihood		167219.180				186678.8172		
PT status: hours-based	**(3) Agreed hours**				**(4) Incl. overtime**			
	Full-time		Part-time		Full-time		Part-time	
Log wages	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Education (years)	0.090	0.001	0.091	0.001	0.092	0.001	0.086	0.001
FT experience (years)	0.030	0.001	0.027	0.001	0.034	0.001	0.028	0.001
FT experience sq.	0.000	0.000	−0.001	0.000	−0.001	0.000	−0.001	0.000
PT experience (years)	0.001	0.001	0.017	0.001	0.000	0.001	0.017	0.001
PT experience sq.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
East	−0.280	0.003	−0.261	0.004	−0.279	0.004	−0.277	0.005
Foreign born	−0.064	0.004	−0.048	0.004	−0.068	0.004	−0.051	0.004
Constant	1.145	0.009	1.060	0.010	0.976	0.010	1.028	0.011
Std.Dev.	0.077	0.001	0.090	0.001	0.093	0.001	0.098	0.001
Hours choice		Coef.	Std.Err.			Coef.	Std.Err.	
Consumption		0.120	0.003			0.149	0.003	
Hours		0.037	0.001			0.035	0.001	
Hours × Kids		0.043	0.001			0.041	0.001	
Hours × East		−0.019	0.001			−0.021	0.001	
Log likelihood		167485.728				186786.764		

Notes: SOEP (2005-2016). Results from full information maximum simulated likelihood (FIMSL) estimation with constant relative risk aversion (CRRA) utility index.

A.4.7 Internal Goodness of Fit

I present graphical evidence of model fit (Figure A.6) and estimated wage elasticities (Table A.12) for the main specification of the discrete choice model with self-reported part-time status and agreed working hours.

Model Fit: Wages and Hours Choices



(a) Hourly Wages

(b) Hours Choices

Figure A.6: Goodness of Fit of the Discrete Choice Model

Wage Elasticities

Estimated elasticities for a one percent increase in gross hourly wage for females in the sample are 0.41 percent for working hours and 0.22 percentage points for participation. These elasticities are mostly within the confidence intervals of comparable estimates by Haan (2006), deviations can be explained by differences in sample composition, most notably I include singles whereas Haan (2006) focuses on married couples.

Table A.12: Labor Supply Elasticities

	Δ Hours (percent)		Δ Participation (p.p.)	
	Coef.	Std.Err.	Coef.	Std.Err.
All women	0.41	0.00	0.22	0.02
By region				
East	0.34	0.00	0.25	0.04
West	0.43	0.00	0.21	0.02

Notes: Predicted changes for a 1% increase in gross hourly wage.

A.4.8 Subgroup Comparison of the Perceived and Observed Returns

Table A.13 presents the point estimates corresponding to the graphical evidence in Figure 1.6 in Section 1.5.4.

Table A.13: Comparison of Expected and Estimated Wage Penalties and Premiums by Subgroups

	Full-time workers				Part-time workers			
	Expected		Estimated		Expected		Estimated	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
All women	0.21	1.27	10.23	0.92	6.70	1.56	−0.10	0.85
Education: Basic	6.85	5.79	10.03	2.18	11.44	5.62	1.60	1.84
Education: Intermediate	−1.54	1.24	9.92	1.21	4.53	1.62	−0.57	1.12
Education: Tertiary	1.46	2.97	10.94	1.84	10.64	3.94	−0.59	1.82
With children	7.10	4.48	5.24	1.54	6.81	1.81	0.41	1.07
Without children	−1.29	1.20	12.50	1.13	6.60	2.38	−0.97	1.39
Age $<$ 40 y.	1.59	2.46	8.77	1.42	6.40	2.45	3.17	1.52
Age $>$ 40 y.	−0.65	1.35	11.15	1.20	6.87	2.01	−1.60	1.02
Eastern Germany	−3.48	1.91	12.76	1.81	7.91	3.66	−1.66	2.06
Western Germany	1.36	1.54	9.26	1.06	6.47	1.72	0.23	0.93
Firm size $>$ 200	1.07	1.81	11.85	1.27	3.77	1.80	0.24	1.25
Firm size $<$ 200	−1.00	1.63	8.52	1.33	10.84	2.50	−0.38	1.16
Fixed term contract	5.46	6.47	10.66	2.59	13.04	5.95	3.75	2.32
Permanent contract	−0.47	1.15	10.43	0.98	5.87	1.60	−0.70	0.91
Manager	13.98	8.12	15.95	3.94	10.48	3.82	2.68	7.37
No Manager	−0.94	1.05	9.88	0.94	6.62	1.58	−0.13	0.85
Tenure $>$ 10 y.	0.05	1.67	15.76	1.52	3.90	2.08	−2.25	1.42
Tenure $<$ 10 y.	0.91	1.92	6.79	1.14	6.99	2.08	1.13	1.06

Notes: SOEP-IS (2016-19) and SOEP (2016). Sample means with standard errors (S.E.) of the expected and estimated part-time wage penalty (full-time workers) and full-time premium (part-time workers) overall and within subgroups. Results based on self-reported part-time status and contractually agreed working hours including overtime. Estimates from the CRRA discrete choice model. Standard errors in SOEP-IS clustered at the person-level.

A.4.9 Nonwage Benefits

Table A.14 shows OLS and fixed effects estimates of changes in nonwage benefits among women switching from full-time to part-time work (full-time leavers) and for women switching from part- to full-time work (part-time leavers).

Table A.14: Changes in Nonwage Benefits among Switchers

	Full-Time Leavers (vs. FT Stayers)		Part-Time Leavers (vs. PT stayers)	
	OLS	FE	OLS	FE
Christmas bonus (EUR/hr)	−0.02	−0.01	0.01	0.02
13th monthly salary (EUR/hr)	−0.06	−0.04	0.13***	0.13**
Vacation bonus (EUR/hr)	0.01	−0.03	0.00	0.01
Profit sharing (EUR/hr)	−0.16	0.12	−1.18	0.13
Public transport/ commuting grant (EUR/hr)	0.03	0.01	−0.01	0.04
Other bonus (EUR/hr)	−0.04	−0.07	−0.02	0.23
Working from home (WFH)	−0.00	−0.03	0.01	0.01
Benefit: Any	−0.06***	0.02	0.05***	0.03
Meals	−0.04**	0.02	0.04**	0.03
Company car	−0.02***	−0.00	0.02**	0.01
Phone	−0.02**	−0.00	0.01	0.01
Charges/ expenses	0.00	0.00	0.02**	0.02*
Computer/ IT	−0.02**	0.01	0.01	0.01
Other benefit	−0.01	0.00	0.01	0.00
Allowances: Any	−0.03	−0.01	0.01	−0.03
Shift/ weekend	−0.01	−0.02	−0.00	−0.04*
Overtime	−0.01	0.01	0.01	0.01
Personal	−0.02**	−0.02*	0.01	−0.00
Gratuity/ Tips	0.00	0.00	−0.00	−0.00
Other allowance	−0.02	−0.00	0.01	−0.02
Christmas bonus	−0.04**	−0.03	−0.02	0.00
13th monthly salary	−0.03*	−0.01	0.01	−0.00
Vacation bonus	−0.03*	0.01	−0.02*	−0.01
Profit sharing	−0.02*	−0.01	−0.01	0.02

Notes: GSOEP-Core 2005-2016. The Table shows coefficient estimates of changes in nonwage benefits for full-time working women who switched to part-time (full-time leavers) and for part-time working women who switched to full-time (part-time leavers), in comparison to stayers. Estimates obtained from multivariate OLS and fixed effects (FE) regression, adjusted for years of education, linear and quadratic work experience in part-time and full-time, region (Eastern/ Western GER), immigrant background, occupation major group (ISCO 88, 1 digit), industry (NACE,2 digit), linear and quadratic tenure and indicators for firm size > 200, public sector and fixed term contract. OLS models additionally contain survey year fixed effects. Estimates are based on women with direct year-to-year transitions between full- and part-time employment. Estimation with robust standard errors (FE) or with standard errors clustered at the person level (OLS), * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In Table A.15, I document how estimated returns to full- and part-time work obtained from the discrete choice model covary with current nonwage benefits. Conditional on worker and job characteristics, full-time workers who currently receive nonwage benefits are predicted to lose less from switching to part-time than comparable workers without benefits. Among part-time workers, those receiving nonwage benefits are predicted to gain over proportionally from switching to full-time. This correlational evidence seems to suggest that workers who receive nonwage benefits tend to work in better jobs and, on top, seem to be positively selected, but correlations are statistically insignificant, so I do not want to overinterpret these results.

Table A.15: Observed Returns and Nonwage Benefits

Dep. Var. =	Full-time workers		Part-time workers	
Predicted FT-PT wage gap in percent	BV	MV	BV	MV
Benefit: Any	−2.75	−2.20	3.31	3.10
Meals	−2.40	−2.85	4.17	3.59
Company car	−0.25	−1.69	5.33	3.81
Phone	−3.03	−3.44	13.01	9.35
Charges/ expenses	−11.60	−9.50	16.95	12.72
Computer/ IT	1.94	2.14	14.54	12.18
Other benefit	−10.43**	−8.93*	4.08	4.05
Allowances: Any	2.15	2.10	2.25	0.84
Shift/ weekend	2.73	2.68	0.10	−2.59
Overtime	6.37	6.48	7.17	3.29
Hardship	11.06	10.25	4.05	−0.89
Personal	5.66	5.59	7.89	5.09
Gratuity/ Tips	5.09	8.49	9.95	10.90
Other allowance	−0.66	−1.00	5.30	5.85
Christmas bonus	2.75	1.28	1.40	3.12
13th monthly salary	1.90	−0.51	−1.66	−0.23
Vacation bonus	2.82	0.77	0.55	2.18
Profit sharing	0.86	−0.12	−0.48	0.61
Public transport/ commuting grant	0.09	0.39	4.37	4.66
Other bonus	4.99	2.07	−5.51	−5.24

Notes: GSOEP-Core 2016. The Table shows coefficient estimates of the structurally estimated part-time wage penalty on various measures of current nonwage benefits. Estimates obtained from bivariate (BV) and multivariate (MV) OLS regressions. Multivariate estimates adjusted for years of education, linear and quadratic work experience in part-time and full-time, region (Eastern/ Western GER), immigrant background, occupation major group (ISCO 88, 1 digit), industry (NACE,2 digit), linear and quadratic tenure and indicators for firm size > 200, public sector and fixed term contract. Estimation with robust standard errors, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix B

Appendix to Chapter 2

B.1 Institutional Context

This section describes key institutional features regarding part-time employment in Germany.

B.1.1 Institutional Context

In 2000, German legislators established a near-universal entitlement to part-time work in the *Act on part-time and temporary work (Teilzeitbefristungsgesetz, TzBfG)*. Since the law became effective in 2001, all workers in German firms with more than 15 employees can demand a reduction in working hours if they have worked at the firm for at least six months (§8 *TzBfG*).[1] Employers can not deny the request to work part-time except for operational reasons, which can be specified in collective agreements.[2] Notably, worker rights to reduce working hours are also established in the *Federal Act on Gender Equality*, which states that employers must accommodate the requests to work part-time of workers at all hierarchical levels, including managers (§16, *Abs.1, BGleiG*).[3] The promotion of flexible hours through legislative efforts has contributed to a vast expansion of part-time work arrangements in the last decades; as of 2021, one in three women and one in ten men in Germany works part-time (OECD, 2022b).

Employers in Germany must not discriminate in pay between full-time and part-time workers unless discrimination is justified by objective reasons. Specifically, equal pay principles in German federal law determine that a 'part-time worker is to be granted remuneration or another divisible compensation that corresponds to at least the proportion of her working time in the working time of a comparable full-time working employee' (§4(1) *TzBfG*). Moreover, part-time workers are equally entitled to statutory sick pay and proportional end-of-year bonuses.[4] In the civil service, the requirement of hours-proportional

[1] *Teilzeit- und Befristungsgesetz* (*TzBfG*), *Act on part-time and temporary work.* Adopted in 2000, last modified in 2019.

[2] In addition, in 2019 the German government established worker rights to reduce working hours only temporarily, for a pre-specified length, but the empirical analyses in this paper use data that was collected before this law was passed (§9*a*, *TzBfG*, *Brückenteilzeit*, German for 'bridging part-time employment'.)

[3] *Bundesgleichstellungsgesetz (BGleiG), Federal Act on Gender Equality.* Adopted in 2015, last modified in 2021.

[4] In the civil service, the requirement of hours-proportional compensation extends to all salary compo-

compensation extends to all salary components, including family allowances, premiums, overseas and hardship allowances and performance bonuses (§6, *Abs.1,BBG*).[5] However, statutory rules explicitly permit differential treatment of part-time and full-time workers when discrimination is justified by objective reasons (§4 *Abs.1, TzBfG*). This ambiguity leaves some wriggle room for employers who can justify different wage rates by pointing to differences in performance that can be hard to measure. In sectors with low unionization where pay is negotiated individually, pay gaps between full-time and part-time workers tend to be larger because workers bargaining over wages forgo the equalizing effects of collective agreements. Moreover, earnings transparency in Germany remains low, facilitating the evasion of equal pay principles.[6] One exception is the public sector where wage tables prescribing hours-proportional pay are openly available. Taken together, the extent to which employers can discriminate in pay between comparable full-time and part-time workers presumably varies across different sectors.

B.2 Survey Questionnaire

B.2.1 Reminder of Hourly Wage

To help respondents in their assessment of counterfactual hourly wages and to improve response precision, individuals first receive an estimate of their current gross hourly wage:

HW A. *The following questions again draw on your income situation. For this purpose, we have used your previous responses regarding your monthly earnings and your contractual working hours and calculated your current gross hourly wage.*

Your current gross hourly wage is [X] Euros.

If individuals did not provide valid responses to either gross monthly income or weekly hours such that hourly wages cannot be calculated, or if the calculated hourly wage is implausibly low (below 7 euros) or high (above 60 euros), individuals do not receive an estimate of their hourly wage but instead are asked to estimate their own hourly wage:

HW B. *What do you think is your current gross hourly wage (without considering overtime hours)? Please think of your contractual working hours and your gross monthly earnings before taxes.*

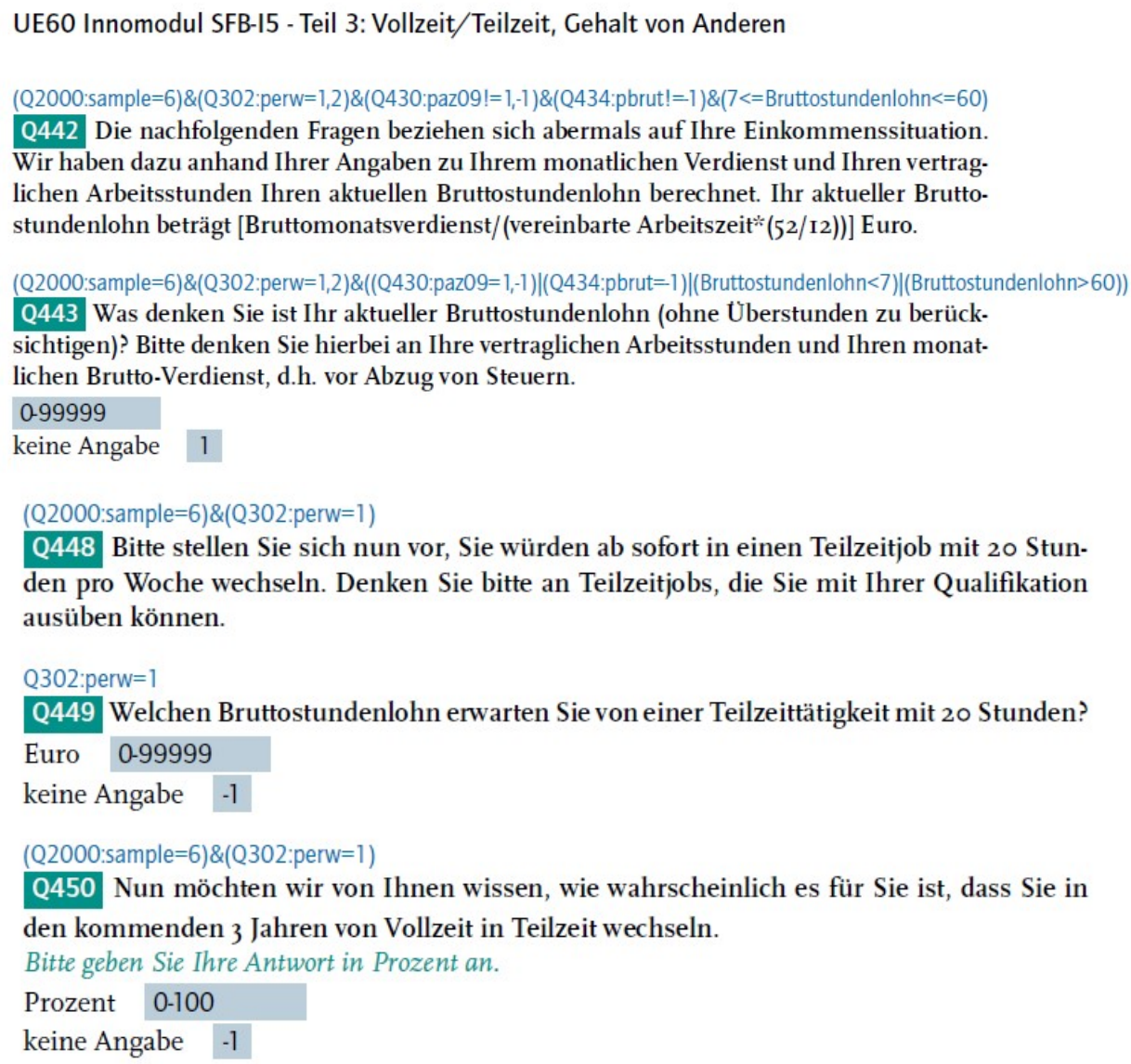
nents, including family allowances, premiums, overseas and hardship allowances and performance bonuses (*Bundesbesoldungsgesetz* (*BBG*), *Federal Salary Act*§6, *Abs.1,BBG*)

[5] *Bundesbesoldungsgesetz* (*BBG*), *Federal Salary Act.* Adopted in 1975, last modified 2021.

[6] Efforts seeking to improve pay transparency have had little bite so far. In 2017, legislators passed the *Transparency of Remuneration Act* (*Entgelttransparenzgesetz*) to improve earnings transparency between men and women, thereby reducing the gender pay gap. However, the complexity of the procedure and the lack of legal consequences explain why, as of 2019, only 0.15 percent of eligible workers had put forward a claim based on the *EntgTranspG* (DJB, 2019).

B.2.2 Original German Questionnaire

This section contains the relevant survey questions from the original German questionnaire of the 2019 GSOEP Innovation Sample survey.



UE60 Innomodul SFB-I5 - Teil 3: Vollzeit/Teilzeit, Gehalt von Anderen

(Q2000:sample=6)&(Q302:perw=1,2)&(Q430:paz09!=1,-1)&(Q434:pbrut!=1)&(7<=Bruttostundenlohn<=60)

Q442 Die nachfolgenden Fragen beziehen sich abermals auf Ihre Einkommenssituation. Wir haben dazu anhand Ihrer Angaben zu Ihrem monatlichen Verdienst und Ihren vertraglichen Arbeitsstunden Ihren aktuellen Bruttostundenlohn berechnet. Ihr aktueller Bruttostundenlohn beträgt [Bruttomonatsverdienst/(vereinbarte Arbeitszeit*(52/12))] Euro.

(Q2000:sample=6)&(Q302:perw=1,2)&((Q430:paz09=1,-1)|(Q434:pbrut=1)|(Bruttostundenlohn<7)|(Bruttostundenlohn>60))

Q443 Was denken Sie ist Ihr aktueller Bruttostundenlohn (ohne Überstunden zu berücksichtigen)? Bitte denken Sie hierbei an Ihre vertraglichen Arbeitsstunden und Ihren monatlichen Brutto-Verdienst, d.h. vor Abzug von Steuern.

0-99999

keine Angabe 1

(Q2000:sample=6)&(Q302:perw=1)

Q448 Bitte stellen Sie sich nun vor, Sie würden ab sofort in einen Teilzeitjob mit 20 Stunden pro Woche wechseln. Denken Sie bitte an Teilzeitjobs, die Sie mit Ihrer Qualifikation ausüben können.

Q302:perw=1

Q449 Welchen Bruttostundenlohn erwarten Sie von einer Teilzeittätigkeit mit 20 Stunden?

Euro 0-99999

keine Angabe -1

(Q2000:sample=6)&(Q302:perw=1)

Q450 Nun möchten wir von Ihnen wissen, wie wahrscheinlich es für Sie ist, dass Sie in den kommenden 3 Jahren von Vollzeit in Teilzeit wechseln.

Bitte geben Sie Ihre Antwort in Prozent an.

Prozent 0-100

keine Angabe -1

Figure B.1: Survey Questionnaire GSOEP-IS 2019 (Full-Time Worker)

(Q2000:sample=6)&(Q302:perw=2)

Q466 Vielen Dank für Ihre Einschätzung zu Ihren Arbeitsstunden. Nun interessiert uns, wie Sie diesbezüglich andere Arbeitnehmer einschätzen.

(Q2000:sample=6)&(Q302:perw=1,2)

Q467 Zur Erinnerung, Ihr eigener geschätzter Bruttostundenlohn beträgt [siehe oben] Euro.

INT: Falls Bruttostundenlohn = 0: Das liegt vermutlich daran, dass die Zielperson in den Vorfragen zum Bruttostundenlohn keine Angabe gemacht hat und somit der Bruttostundenlohn nicht berechnet werden konnte.

(Q2000:sample=6)&(Q302:perw=1,2)

Q468 Was denken Sie ist der Bruttostundenlohn durchschnittlicher Teilzeit-Arbeitnehmer in Ihrem Beruf?

Euro	0-99999
keine Angabe	-1

(Q2000:sample=6)&(Q302:perw=1,2)

Q469 Was denken Sie ist der Bruttostundenlohn durchschnittlicher Vollzeit-Arbeitnehmer in Ihrem Beruf?

Euro	0-99999
keine Angabe	-1

(Q2000:sample=6)&(Q302:perw=1,2)

Q470 Dummy

Gruppe A	1
Gruppe B	2

(Q2000:sample=6)&(Q302:perw=1,2)

Q471 Nehmen Sie nun an, ein durchschnittlicher Teilzeit-Arbeitnehmer in Ihrem Beruf, der momentan einen Bruttostundenlohn von [ISFB2019_17] Euro erhält, wechselt auf eine Vollzeitstelle. Welchen Bruttostundenlohn erwarten Sie für diesen Arbeitnehmer in Vollzeit?

Euro	0-99999
keine Angabe	-1

(Q2000:sample=6)&(Q302:perw=1,2)

Q472 Betrachten wir nun den entgegengesetzten Fall

(Q2000:sample=6)&(Q302:perw=1,2)

Q473 Nehmen Sie nun an, ein durchschnittlicher Vollzeit-Arbeitnehmer in Ihrem Beruf, der momentan einen Bruttostundenlohn von [ISFB2019_18] Euro erhält, wechselt auf eine Teilzeitstelle. Welchen Bruttostundenlohn erwarten Sie für diesen Arbeitnehmer in Teilzeit?

Euro	0-99999
keine Angabe	-1

Figure B.2: Survey Questionnaire GSOEP-IS 2019 (Full-Time Worker, Continued)

UE59 Innomodul Stundenlohn

(Q302:perw=1,2)&(Q2000:sample=1:5)&(Q430:paz09!=1,-1)&(Q434:pbrut!=1)

Q435 Die nachfolgenden Fragen beziehen sich abermals auf Ihre Einkommenssituation. Wir haben dazu anhand Ihrer Angaben zu Ihrem monatlichen Verdienst und Ihren vertraglichen Arbeitsstunden Ihren aktuellen Bruttostundenlohn berechnet.
Ihr aktueller Bruttostundenlohn beträgt [Bruttomonatsverdienst/(vereinbarte Arbeitszeit*(52/12))] Euro.

(Q302:perw=1,2)&(Q2000:sample=1:5)&((Q430:paz09=-1)|(Q434:pbrut=-1))

Q436 Was denken Sie ist Ihr aktueller Bruttostundenlohn (ohne Überstunden zu berücksichtigen)? Bitte denken Sie hierbei an Ihre vertraglichen Arbeitsstunden und Ihren monatlichen Brutto-Verdienst, d.h. vor Abzug von Steuern.

0-99999
keine Angabe -1

(Q302:perw=1,2)&(Q2000:sample=1:5)

Q437 Dummy

Kein Treatment 1
Treatment 1 2
Treatment 2 3

Q437:isl_dummy=2

Q438 Studien zeigen, dass durchschnittliche Vollzeit-Beschäftigte in Deutschland etwa 20% mehr pro Stunde verdienen als durchschnittliche Teilzeit-Beschäftigte pro Stunde.

Q437:isl_dummy=3

Q439 Studien zeigen, dass durchschnittliche Vollzeit-Beschäftigte in Deutschland etwa 20% mehr pro Stunde verdienen als durchschnittliche Teilzeit-Beschäftigte pro Stunde. Dieser Lohnunterschied kann jedoch größtenteils dadurch erklärt werden, dass Vollzeit-Beschäftigte im Durchschnitt mehr Arbeitserfahrung haben.

(Q302:perw=1,2)&(Q2000:sample=1:5)&(Q302:perw=1)

Q440 Bitte stellen Sie sich nun vor, Sie würden ab sofort in einen Teilzeitjob mit 20 Stunden pro Woche wechseln. Denken Sie bitte an Teilzeitjobs, die Sie mit Ihrer Qualifikation ausüben können. Welchen Bruttostundenlohn erwarten Sie von einer Teilzeittätigkeit mit 20 Stunden?

Euro 0-99999
keine Angabe 1

(Q302:perw=1,2)&(Q2000:sample=1:5)&(Q302:perw=2)

Q441 Bitte stellen Sie sich nun vor, Sie würden ab sofort in einen Vollzeitjob mit 40 Stunden pro Woche wechseln. Denken Sie bitte an Vollzeitjobs, die Sie mit Ihrer Qualifikation ausüben können. Welchen Bruttostundenlohn erwarten Sie von einer Vollzeittätigkeit mit 40 Stunden?

Euro 0-99999
keine Angabe 1

Figure B.3: Information Experiment GSOEP-IS 2019

B.3 Data

B.3.1 Sample

Table B.1: Sample Characteristics in GSOEP Innovation Sample

GSOEP Innovation Sample	Main Sample (1)	Experiment (2)
Part-time employed	26.9	27.3
Female	44.1	47.2
Education: Basic	20.2	18.7
Education: Middle	49.7	55.7
Education: University	30.1	25.6
Hourly wage (in euros)	19.7	20.1
Age (in years)	42.5	43.8
Eastern Germany	13.9	18.4
Public sector	25.0	25.8
Firm size > 200	59.6	54.6
Occupational Area:		
1. Agriculture, Forestry, Farming etc.	2.1	2.0
2. Raw Materials, Goods, Manufacturing	18.0	18.2
3. Construction, Architecture, Technical Building	6.6	4.2
4. Natural Sciences, Geography, Informatics	7.0	4.5
5. Traffic, Logistics, Safety, Security	13.2	12.5
6. Commercial Services, Trading, Tourism etc.	9.6	11.6
7. Business Organization, Accounting, Law etc.	16.2	21.9
8. Health Care, Social Sector, Teaching etc.	24.4	22.3
9. Philology, Literature, Humanities etc.	2.9	2.7
Survey years	2016-19	2019
Observations	1,362	1,425

Notes. GSOEP 2016-19. Means weighted. Occupation defined by 1-digit KldB 2010.

B.3.2 Survey Experiment

Table B.2: Experimental Sample Statistics

	Raw data	Full sample		Estimation sample	
	N	*N*	% (Raw)	N	% (Full)
Treatment T1	512	457	89.3	275	60.2
Treatment T2	550	506	92.0	339	67.0
Control	522	462	88.5	286	61.9
Total	1,584	1,425	90.0	900	63.2

Notes. GSOEP 2019. Full sample after sample restrictions. Estimation sample after excluding missing and invalid responses in hours, actual and expected wages.

Table B.3: Survey Experiment: Sample Characteristics by Randomization Status

	Mean				Diff.	p-val	Diff.	p-val	Diff.	p-val	Diff.	p-val
A. Raw data	C	T1	T2	Treat	T1 - C		T2 - C		Treat - C		T2 - T1	
Part-time employed	0.250	0.267	0.291	0.279	0.017	0.660	0.040	0.297	0.029	0.379	0.024	0.556
Female	0.461	0.440	0.486	0.464	−0.021	0.632	0.025	0.569	0.003	0.939	0.046	0.290
Education: Basic	0.206	0.180	0.166	0.172	−0.026	0.469	−0.040	0.235	−0.034	0.280	−0.015	0.652
Education: Middle	0.517	0.555	0.567	0.561	0.038	0.391	0.050	0.254	0.044	0.248	0.012	0.783
Education: University	0.277	0.265	0.268	0.266	−0.012	0.756	−0.009	0.812	−0.010	0.754	0.003	0.945
Hourly wage (in euros)	20.583	19.373	20.260	19.855	−1.210	0.148	−0.323	0.707	−0.728	0.331	0.887	0.269
Age (in years)	45.772	43.951	43.277	43.600	−1.821	0.100	−2.495	0.014	−2.173	0.018	−0.674	0.529
Eastern Germany	0.170	0.196	0.180	0.188	0.026	0.386	0.010	0.723	0.018	0.481	−0.016	0.609
Public sector	0.224	0.223	0.263	0.244	−0.002	0.958	0.039	0.287	0.019	0.531	0.040	0.274
Firm size > 200	0.541	0.539	0.569	0.555	−0.002	0.962	0.028	0.545	0.014	0.736	0.030	0.515
Observations	522	512	550									
B. Estimation sample	C	T1	T2	Treat	T1 - C		T2 - C		Treat - C		T2 - T1	
Part-time employed	0.246	0.217	0.264	0.244	−0.029	0.562	0.018	0.719	−0.002	0.965	0.047	0.366
Female	0.487	0.403	0.504	0.462	−0.084	0.147	0.017	0.763	−0.025	0.611	0.101	0.076
Education: Basic	0.203	0.172	0.159	0.164	−0.031	0.527	−0.045	0.310	−0.039	0.333	−0.014	0.765
Education: Middle	0.512	0.524	0.591	0.563	0.013	0.827	0.080	0.152	0.052	0.296	0.067	0.240
Education: University	0.285	0.303	0.250	0.272	0.018	0.732	−0.035	0.473	−0.013	0.771	−0.053	0.290
Hourly wage (in euros)	21.516	20.595	20.109	20.306	−0.920	0.354	−1.406	0.160	−1.210	0.171	−0.486	0.606
Age (in years)	43.104	43.061	43.523	43.331	−0.043	0.973	0.419	0.733	0.226	0.837	0.463	0.707
Eastern Germany	0.147	0.190	0.159	0.172	0.043	0.285	0.012	0.728	0.025	0.428	−0.031	0.451
Public sector	0.233	0.193	0.307	0.260	−0.040	0.365	0.073	0.120	0.026	0.512	0.113	0.016
Firm size > 200	0.603	0.565	0.553	0.558	−0.038	0.501	−0.050	0.355	−0.045	0.340	−0.012	0.835
Observations	286	275	339									

Notes. GSOEP 2019. Means weighted. C= Control group, T1= Correlation treatment, T2=Correlation/de-biasing treatment. Treat = T1+T2. P-values from robust two sample mean-comparison tests.

B.4 Research Design

B.4.1 German Classification of Occupations (KldB 2010)

Table B.4 presents the structure of the German Classification of Occupations (KldB 2010), with broad (1-digit) to skill-specific (5-digit) levels of aggregation.

Table B.4: German Classification of Occupations (KldB 2010) - Structure

Digit Level	Breakdown Level	No. of Levels	Example (Classification Title)	Example (Code)
1	Occupational Area	10	Production of raw materials and goods, manufacturing	2
2	Occupational Main Group	37	Metal-making and working, metal construction	24
3	Occupational Group	144	Metalworking	242
4	Occupational Sub-Group	700	Non-cutting	2421
5	Occupational Type	1286	Skilled tasks	24212

Source: Statistik der Bundesagentur für Arbeit. German Classification of Occupations 2010. Own representation.

In Table B.5, I illustrate how I define occupational reference groups by providing examples of occupational definitions at different digit levels.

Table B.5: German Classification of Occupations (KldB 2010) - Examples

1 digit	**Health Care, Social Sector, Teaching, Education (8)**			
2 digit	Medical and Health Care (81)			
3 digit	**Nursing, emergency medical services, obstetrics (813)**		**Human medicine and dentistry (814)**	
4 digit	Emergency medical services (8134)	Obstetrics, maternity care (8135)	Pediatrics and adolescent medicine (8141)	Dentists and orthodontists (8147)
5 digit	*Unskilled/ semi-skilled (81341)* *Skilled (81342)* *Complex (81343)*	*Skilled (81352)* *Complex (81353)*	*Highly complex (81414)*	*Highly complex (81474)*
2 digit	Teaching and Training (84)			
3 digit	**Vocational schools and training (842)**		**Driving, flying, sports instructors (845)**	
4 digit	Teachers for occupation-specific subjects at vocational schools (8421)	In-company instructors in vocational training (8422)	Driving instructors (8451)	Coaches in ball sports (8454)
5 digit	*Complex (84213)* *Highly complex (84214)*	*Complex (84223)* *Highly complex (84224)*	*Complex (84513)*	*Complex (84543)*

Source: Statistik der Bundesagentur für Arbeit. German Classification of Occupations 2010. Own representation.

B.4.2 Alternative Measures of the Corrected Part-Time Wage Gap

In the main analyses, selectivity-corrected part-time wage gaps are based on occupation-specific Blinder-Oaxaca-decompositions of the part-time wage gap (Section 2.3.4). This section describes alternative approaches of measuring selectivity-corrected part-time wage gaps.

Wage changes of switchers A different approach to measure the causal ATT_{R_i} is to use the actual wage changes of workers who switched between full-time and part-time jobs. Exploiting the longitudinal depth of the GSOEP, I construct occupation-specific estimates of the ATT_{R_i}s based on within-variation as an alternative proxy of the true part-time wage effect.[7] By conditioning on wage changes following switches, I address the concern

[7]The estimates are obtained separately for each 3-digit KldB2010 occupation code based on robust

of selection on unobservables because the ATT_{R_i}s are identified using person fixed effects. However, identification based on switchers does not yield the ATT when switchers differ from the population of interest and, indeed, there is evidence that switchers are not representative. One problem is for instance that only few male workers switch between full-and part-time work; hence, the ATT_{R_i}s are mostly identified based on women. And even among women, switchers represent a select group (Schrenker, 2022). The main challenge in computing a plausible proxy of the part-time wage effect for an average worker is that the workers we observe switching between full- and part-time employment do not represent the average worker. On top of this, using wage changes of switchers does not solve the concern imposed by heterogeneous treatment effects.

In a set of robustness analyses, I use longitudinal data from the core GSOEP to estimate wage changes following switches between full- and part-time employment. The core GSOEP is larger than the SOEP-IS and has a longer panel dimension, which I exploit to estimate wage changes on the occupational level. I use longitudinal information between 2010-2019 from GSOEP wave v36, yielding 43,733 observations from approximately 9,800 individuals. I match core GSOEP and SOEP-IS data based on KldB occupation codes (match rate based on 3-digit *KldB2010* for the SOEP-IS sample is 98.2 percent).

Linear wages in public sector and civil service An alternative way of thinking about the causal ATT_{R_i} is by adopting the employer's perspective. By law, German firms must not discriminate between part-time and full-time workers (see Section B.1.1). In reality, the extent to which employers can pay workers different wages and obfuscate differences in pay varies across firms and sectors. Importantly, it depends strongly on the adoption of collective agreements. One sector of the German economy where discriminatory pay based on hours worked is essentially impossible is the public sector. In public sector occupations, as well as in the civil service, salaries are set based on publicly available pay scales, and working time reductions automatically come with proportional reductions of all salary components including performance-based allowances. Accordingly, the causal ATT_{R_i} should be equivalent to zero in public sector occupations. Likewise, heterogeneous treatment effects are essentially ruled out.[8] I exploit this in the sensitivity analyses by separately investigating the beliefs of workers in public sector employment, assuming that the true causal effect of part-time work on wages in these occupations equals zero.

B.4.3 Belief Types

In learning from other workers' outcomes, individuals may differ in their ability to account for selection effects. However, estimates of Equation 2.2 only indicate average responses to group differences. To further analyze the extent of disagreement in worker beliefs, as well as the determinants of beliefs biases, I distinguish workers by classifying three broad belief types:

fixed effects regressions of log hourly wage on part-time status with controls for age, years of education, tenure, children, marital status, and region, using panel waves 2010-2019 from the core GSOEP (see Section 2.3.5 for additional information about the data). Occupations with fewer than 100 observations are dropped.

[8]There is some evidence that performance bonuses are becoming increasingly important in public sector occupations, driving a wedge between the average earnings of men and women in the civil service (Detmer, 2021). Similarly, public sector employers could circumvent hours-proportional pay by disproportionately rewarding full-time employees with incentive bonuses.

$$\begin{aligned}
&\textbf{Type I} && \text{if } \tilde{E}[Y_{FT,i} - Y_{PT,i}|FT] \in (ATT_{R_i} - \iota, ATT_{R_i} + \iota),\\
&\textbf{Type II} && \text{if } \tilde{E}[Y_{FT,i} - Y_{PT,i}|FT] > ATT_{R_i} + \iota,\\
&\textbf{Type III} && \text{if } \tilde{E}[Y_{FT,i} - Y_{PT,i}|FT] < ATT_{R_i} - \iota.
\end{aligned}$$

where ι denotes a constant tolerance parameter specifying the permissible deviation from the ATT_{R_i}. Under the assumption that true part-time wage effects $E[Y_{FT,i} - Y_{PT,i}]$ are constant *within* worker peer groups, $E[Y_{FT,i} - Y_{PT,i}] = ATT_{R_i}\ \forall i \in \{1, ..., N\}$, beliefs of Type I are consistent with *rationality*.[9] Likewise, with constant within-peer-group treatment effects, Type-II beliefs are consistent with *selection neglect*.[10] Finally, Type-III beliefs are consistent with *overoptimism* (full-time workers) or *overpessimism* (part-time workers), respectively.

B.5 Additional Results

B.5.1 Part-Time Wage Gaps and Worker Selection

Table B.6: Part-Time Employment Shares by Gender and Education across Occupational Areas

	Overall			No degree			Vocational degree			University degree		
	Total	Men	Women	Total	Men	Women	Total	Men	Women	Total	Men	Women
All workers	32.0	12.7	54.4	40.6	21.7	63.4	30.7	8.90	54.9	26.1	11.1	43.7
1. Agriculture, Forestry, Farming etc.	19.7	11.9	45.3	13.1	9.4	36.9	19.0	10.1	44.8	10.5	4.1	37.3
2. Raw Materials, Goods, Manufacturing	11.9	7.0	36.6	18.9	11.8	34.9	9.1	5.1	35.6	9.1	5.6	27.1
3. Construction, Architecture, Technical Building	13.7	11.5	44.5	16.8	14.9	66.0	9.5	7.9	48.0	17.4	8.9	38.1
4. Natural Sciences, Geography, Informatics	14.2	8.5	34.2	25.4	22.4	34.3	12.8	6.7	34.7	14.0	8.3	33.8
5. Traffic, Logistics, Safety, Security	31.3	16.2	63.5	45.2	24.1	73.7	21.5	10.2	53.6	13.9	6.2	34.1
6. Commercial Services, Trading, Tourism etc.	45.2	19.5	61.2	63.8	47.9	71.0	41.8	11.6	59.3	19.7	8.0	36.3
7. Business Organization, Accounting, Law etc.	34.2	10.4	48.7	46.7	25.0	61.7	37.8	9.0	50.5	23.7	8.2	39.9
8. Health Care, Social Sector, Teaching etc.	53.8	29.0	60.8	69.3	57.7	72.1	57.6	29.9	62.5	42.3	24.8	52.1
9. Philology, Literature, Humanities etc.	28.9	17.2	40.1	43.9	35.8	53.6	30.0	15.2	44.3	23.8	12.6	33.5

Notes. VSE 2018. Cells contain part-time shares in percent. Occupational areas based on 1-digit KldB 2010 (German classification of occupations). Means weighted.

[9] I refer to Type-I beliefs as being consistent with rationality. However, it is worth noting that it is difficult to classify beliefs *ex-post* as rational because individuals may hold beliefs that are objectively consistent with rationality but may be the result of lucky guessing. Likewise, in scenarios where the ATT_{R_i} is zero, Type I beliefs are also consistent with an anchoring heuristic or naiveté, such as when individuals anchor their beliefs about the counterfactual wage outcome at their current factual wage.

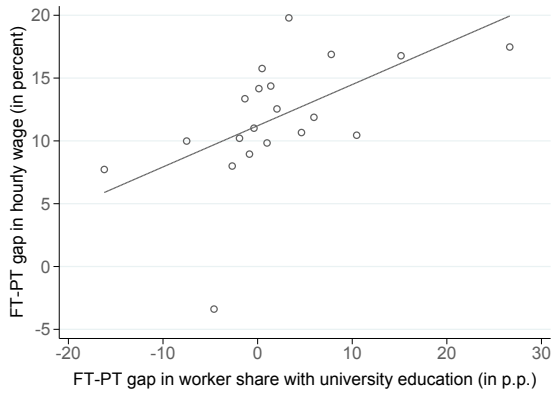
[10] For part-time workers who form beliefs about switching to full-time, Type II-beliefs are consistent with both selection neglect and overconfidence (see the related discussion in Barron et al. (2019) on separate identification of selection neglect and overconfidence), whereas selection neglect and overconfident types are separately identified for full-time workers who form beliefs about switching to part-time.

Table B.7: Part-Time Wage Gaps and Worker Selection across Occupational Areas

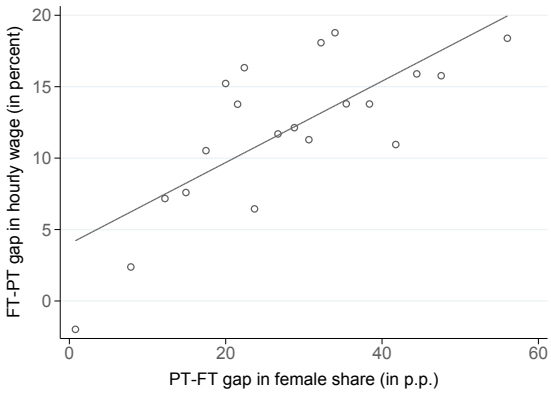
	Log hourly wage			University degree (percent)			Tenure (years)			Managerial position (percent)		
	FT	PT	Diff.	FT	PT	Diff.	FT	PT	Diff.	FT	PT	Diff.
All workers	2.987	2.768	0.219	20.8	15.6	5.2	11.6	10.8	0.8	6.5	1.8	4.7
1. Agriculture, Forestry, Farming etc.	2.707	2.471	0.236	11.7	5.6	6.1	10.1	6.1	4.0	2.5	1.2	1.3
2. Raw Materials, Goods, Manufacturing	2.986	2.682	0.304	10.1	7.5	2.6	11.4	8.7	2.7	5.5	2.7	2.8
3. Construction, Architecture, Technical Building	2.858	2.684	0.173	10.3	13.7	−3.4	10.0	6.8	3.2	6.9	2.7	4.2
4. Natural Sciences, Geography, Informatics	3.261	3.105	0.156	39.4	38.8	0.6	9.9	10.9	−1.0	4.1	1.5	2.6
5. Traffic, Logistics, Safety, Security	2.738	2.533	0.205	8.8	3.1	5.7	10.8	9.4	1.4	2.2	0.6	1.6
6. Commercial Services, Trading, Tourism etc.	2.907	2.548	0.359	11.2	3.3	7.8	8.7	7.5	1.2	10.4	1.6	8.8
7. Business Organization, Accounting, Law etc.	3.152	2.899	0.253	33.6	20.1	13.5	14.6	14.9	−0.3	10.5	2.3	8.2
8. Health Care, Social Sector, Teaching etc.	3.037	2.892	0.145	38.2	24.0	14.2	12.1	11.0	1.1	5.6	1.8	3.8
9. Philology, Literature, Humanities etc.	3.083	2.843	0.240	37.7	28.9	8.8	7.9	7.8	0.1	4.2	1.4	2.8

Notes. VSE 2018. Cells contain weighted sample means for full-time (FT) and part-time (PT) workers and differences in means (Diff.). Occupational area based on 1-digit KldB 2010 (German classification of occupations).

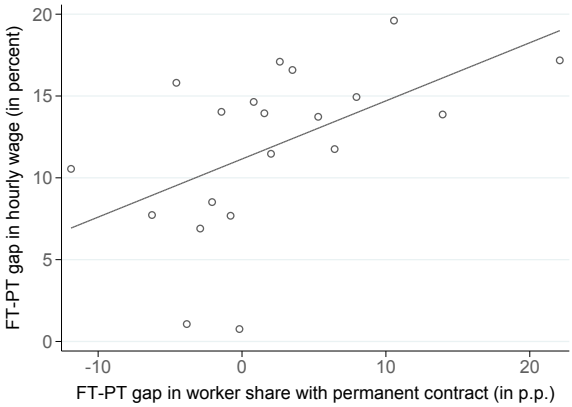
(a) **Wage gap vs. education gap**
Diff. full-/part-time by occupation



(b) **Wage gap vs. gender gap**
Diff. full-/part-time by occupation



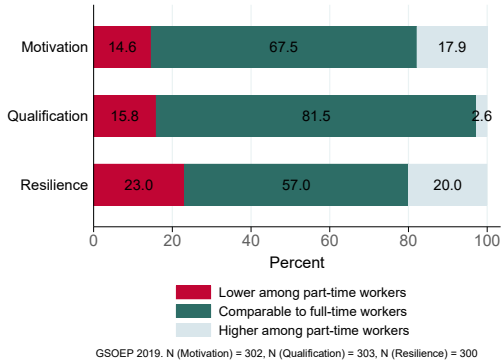
(c) **Wage gap vs. permanent contract gap**
Diff. full-/part-time by occupation



Notes: Binned scatter with linear fit of the raw part-time wage gap plotted against the full-time/part-time gaps in worker education (panel a), worker sex (panel b), and worker share with permanent contract (panel c), by occupation. Occupation based on 3-digit KldB 2010. Data source: VSE 2018.

Figure B.4: Part-Time Wage Gaps and Worker Selection within Occupation

B.5.2 Perceived Relative Productivity of Part-Time Workers

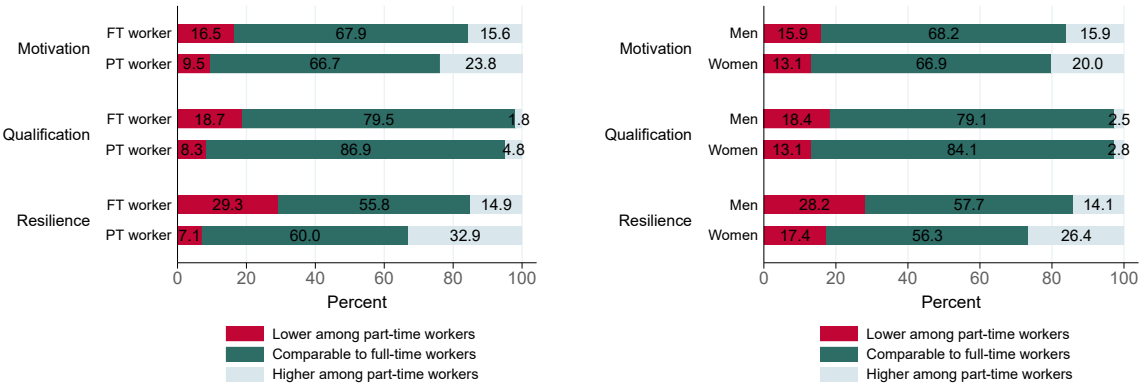


Notes: Plot shows the fraction of workers stating that the motivation, the qualification, and the resilience of part-time workers is lower, comparable, or higher among part-time workers in comparison to full-time workers. Data source: SOEP-IS 2019.

Figure B.5: Perceived Relative Productivity of Part-Time Workers

(a) By employment status

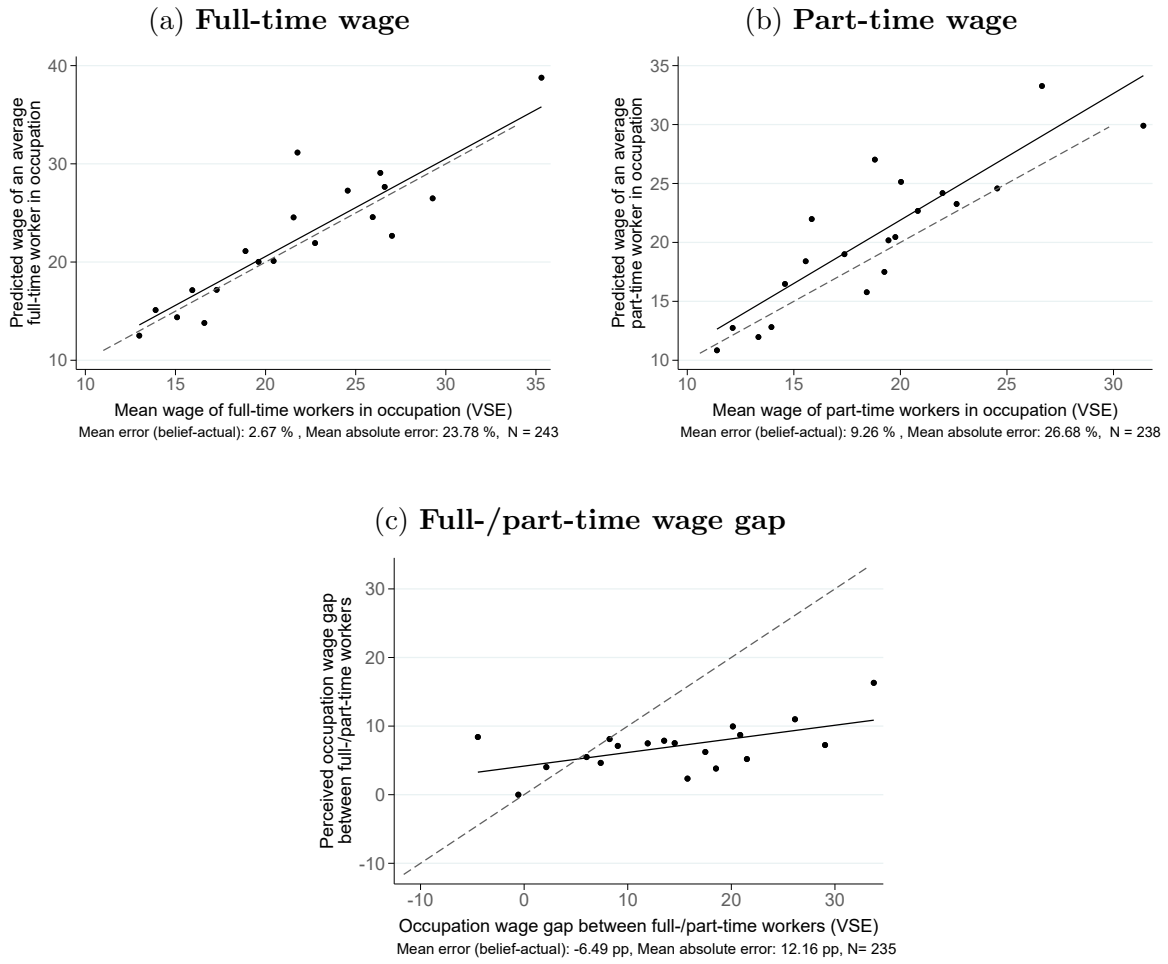
(b) By gender



Notes: Plots show the fraction of workers stating that the motivation, the qualification, and the resilience of part-time workers is lower, comparable, or higher among part-time workers in comparison to full-time workers, separately by employment status (panel a) and by gender (panel b). Data source: SOEP-IS 2019.

Figure B.6: Perceived Relative Productivity of Part-Time Workers by Subgroups

B.5.3 Worker Misperceptions about Average Full- and Part-Time Wages



Notes: Binned scatter with linear fit of perceived and true occupational full-time wages (panel a), part-time wages (panel b), and the full-/part-time wage gap (panel c). Dashed 45-degree line benchmarks correct beliefs. Occupation based on 3-digit KldB 2010. Data sources: GSOEP 2019 (beliefs), VSE 2018 (benchmarks).

Figure B.7: Worker Misperceptions about Average Part-Time Pay Gaps

B.5.4 OLS Estimates of Self-Beliefs about the Part-Time Penalty

Table B.8: OLS: Self-Beliefs about the Part-Time Penalty

	(1) Full-time workers		(2) Part-time workers	
Female	0.12	(1.81)	3.29	(3.10)
Age (in years)	−0.05	(0.07)	−0.17	(0.12)
Eastern Germany	−0.63	(1.99)	1.86	(2.57)
Education: Middle	−0.26	(2.13)	−5.34	(4.08)
Education: University	0.49	(2.22)	−4.33	(4.77)
Public sector	−4.76***	(1.72)	−2.47	(2.28)
Firm size > 200	2.90*	(1.52)	−6.57***	(2.20)
Occupational Area (Ref.: 1. Agriculture)				
2. Raw Materials, Goods, Manufacturing	11.00**	(5.50)	9.94	(8.87)
3. Construction, Architecture, Technical Building	10.22*	(5.80)	4.95	(6.68)
4. Natural Sciences, Geography, Informatics	9.93*	(5.83)	−0.89	(8.09)
5. Traffic, Logistics, Safety, Security	11.14*	(5.81)	0.74	(6.64)
6. Commercial Services, Trading, Tourism etc.	3.55	(6.03)	0.30	(6.66)
7. Business Organization, Accounting, Law etc.	8.85	(5.58)	2.25	(6.62)
8. Health Care, Social Sector, Teaching etc.	9.28	(5.67)	0.93	(6.45)
9. Philology, Literature, Humanities etc.	5.95	(7.49)	−0.67	(7.43)
Observations	634		288	

Notes. GSOEP 2016-19. Dependent variable is the self-expected wage loss for a switch from full-time to part-time (full-time workers) or wage gain for a switch from part-time to full-time (part-time workers) in percent. Reference category for education is basic education. Standard errors clustered at the person level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.5.5 Belief Types

A classification of workers into different belief types based on workers' self-beliefs (Table B.9) reveals that approximately 12 percent of workers hold beliefs that are consistent with rationality (Type I). Among full-time workers, 14 percent hold beliefs that are consistent with selection neglect (Type II), and a vast majority is overconfident (Type III). For part-time workers, selection neglect and overoptimism are not separately identified; jointly these beliefs constitute 36 percent of workers.

Table B.9: Belief Types based on Self-Beliefs about the Part-Time Penalty

$\tilde{E}$ = Self-beliefs PT penalty	All workers	FT workers	PT workers
Type I	11.68	11.51	12.00
Type II	21.50	13.67	36.00
Type III	66.82	74.82	52.00
N	214	139	75

Notes. GSOEP 2019 (I5). Cells contain shares in percent. Type I: $\tilde{E}_i \in (ATT_{R_i} - \iota, ATT_{R_i} + \iota)$, Type II: $\tilde{E}_i > ATT_{R_i} + \iota$, Type III: $\tilde{E}_i < ATT_{R_i} - \iota$, with tolerance $\iota = 2$ percent and corrected occupation group part-time wage gap ATT_{R_i} based on the VSE 2018 and 3-digit occupation codes (KldB 2010).

Table B.10 presents belief types based on predicted wage losses for an average full-time

worker switching to part-time (Panel A) and predicted wage gains for an average part-time worker switching to full-time (Panel B).

Table B.10: Belief Types based on Predicted Losses and Gains for an Average Worker

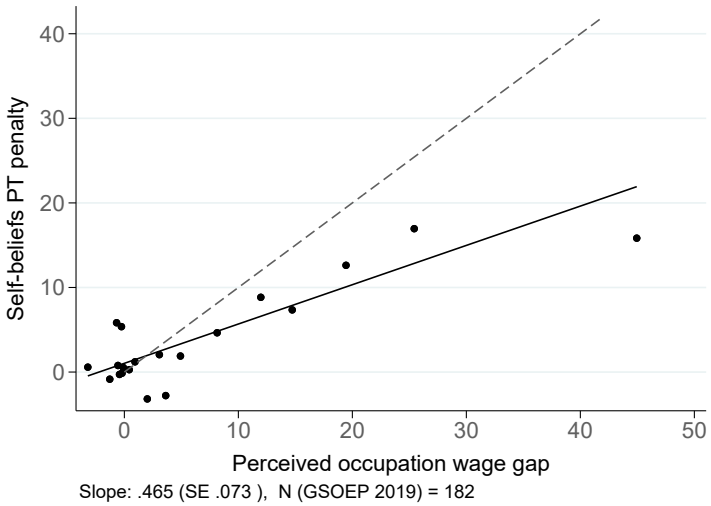
A) $\tilde{E}$ = PT loss FT worker	All workers	FT workers	PT workers
Type I	15.22	18.42	8.97
Type II	20.43	15.79	29.49
Type III	64.35	65.79	61.54
N	230	152	78
B) $\tilde{E}$ = FT gain PT worker	All workers	FT workers	PT workers
Type I	15.25	17.81	10.39
Type II	29.15	26.71	33.77
Type III	55.61	55.48	55.84
N	223	146	77

Notes. GSOEP 2019 (I5). Cells contain shares in percent. Type I: $\tilde{E}_i \in (ATT_{R_i} - \iota, ATT_{R_i} + \iota)$, Type II: $\tilde{E}_i > ATT_{R_i} + \iota$, Type III: $\tilde{E}_i < ATT_{R_i} - \iota$, with tolerance $\iota = 2$ percent and corrected occupation group part-time wage gap ATT_{R_i} based on the VSE 2018 and 3-digit occupation codes (KldB 2010).

B.5.6 Robustness: Wage Changes following Switches between Full-Time and Part-Time Employment

To investigate the sensitivity of my findings to alternative specifications of the corrected part-time penalty, I replicate all analyses, replacing cross-sectional estimates obtained from decomposition analyses with longitudinal estimates based on wage changes following actual switches between full-time and part-time employment (see Section B.4.2). Estimates of the corrected part-time penalty using within-variation in wages among switchers yields smaller estimates of the corrected part-time penalty than cross-sectional estimates, leading to a larger fraction of Type-I belief types as well as moderate increases in the share of individuals with Type-II beliefs that are consistent with selection neglect and/or overconfidence (Table B.11). Slope estimates of self-beliefs with respect to the perceived raw part-time wage gap are similar to the main specification when conditioning on corrected part-time penalties based on switchers, with an elasticity of 0.465 (Figure B.8), corroborating the conclusion that individuals account only insuffiently for selection effects in the context of the part-time penalty.

In Table B.11, I present a classification into belief types based on estimates of the corrected part-time penalty from wage changes following switches.



Notes: Binned scatter with linear fit of the self-expected causal part-time penalty plotted against the perceived raw occupational wage gap between full-time and part-time workers, residualized for corrected occupation part-time wage gaps based on wage changes following switches. Dashed 45-degree line benchmarks full selection neglect. Occupation based on 3-digit KldB 2010. Data sources: GSOEP-IS 2019 (beliefs), VSE 2018 (raw gaps), GSOEP 2010-2019 (corrected gaps).

Figure B.8: Perceived Causal and Raw Part-Time Wage Gaps based on Wage Changes following Switches

Table B.11: Belief Types based on Wage Changes following Switches

$\tilde{E}$ = Self-beliefs PT penalty	All workers	FT workers	PT workers
Type I	61.27	62.88	58.33
Type II	31.37	25.76	41.67
Type III	7.35	11.36	0.00
N	204	132	72

Notes. GSOEP 2019 (I5). Cells contain shares in percent. Type I: $\tilde{E}_i \in (ATT_{R_i} - \iota, ATT_{R_i} + \iota)$, Type II: $\tilde{E}_i > ATT_{R_i} + \iota$, Type III: $\tilde{E}_i < ATT_{R_i} - \iota$, with tolerance $\iota = 2$ percent and corrected occupation group part-time wage gap ATT_{R_i} based on GSOEP estimates of wage changes following switchers and 3-digit occupation codes (KldB 2010).

B.5.7 Robustness: Linear Wages in the Public Sector

The linear wage mandate in public sector occupations allows me to study if workers mislearn from average pay gaps in a setting where true causal part-time penalties are essentially ruled out. A separate analysis of public sector workers reveals that public sector employees, including civil servants, also expect small part-time wage penalties between 3.3 and 3.6 percent (Table B.12). Moreover, the beliefs of public sector workers about the part-time penalty also correlate with perceived raw pay gaps in their occupation (Slope = 0.7, see Figure B.9). A classification of public sector workers into different belief types further shows that although a majority rationally expects near-linear wages (Type I), a non-negligible share of workers holds Type-II-beliefs consistent with selection neglect and/or overconfidence, with estimates ranging between 13 to 19 percent (Table B.13). Taken together, I document that workers expect part-time pay penalties even in occupations with linear wage mandates and that these beliefs correlate with perceptions about raw peer group wage gaps, as hypothesized by selection neglect theory.

In Table B.12, I show sample means and standard deviations of worker self-beliefs about the part-time penalty separately for public sector employees. Given limited sample size, I pool individuals from GSOEP-IS Sample I5 together with individuals from the experimental control group who receive the identical question on self-beliefs.

Table B.12: Public Sector Employees: Self-Beliefs about the Part-Time Penalty

	Public sector		Excl. civil servants		Civil servants	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Self-beliefs PT penalty	3.65	13.72	3.74	13.27	3.32	15.38
(S.E.)	(1.16)		(1.27)		(2.72)	

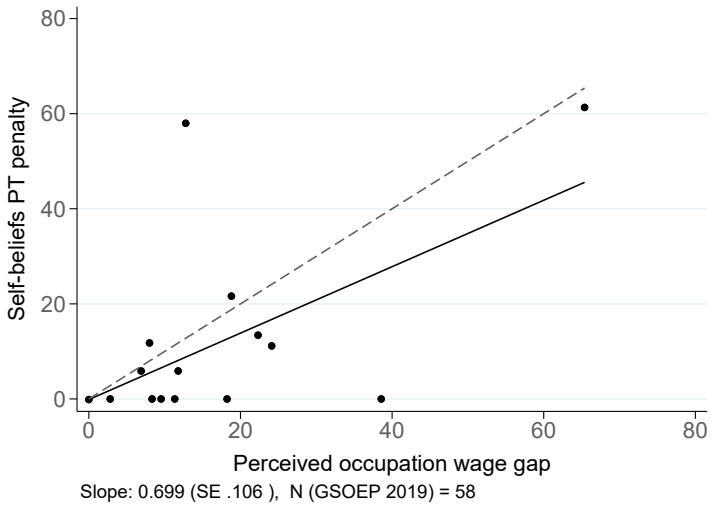
Notes. GSOEP-IS 2019, N (all public sector employees)= 223, N (excl. civil servants)= 166, N (civil servants)= 57. Cells contain perceived causal part-time wage penalties for a switch between working full-time (FT) and part-time (PT) in percent. S.E. = standard error, S.D. = standard deviation.

In Table B.13, I present a classification into different belief types separately for public sector employees, based on the pooled sample and self-beliefs about the part-time wage penalty. In line with the linear wage mandate, the rational benchmark for public sector employees is set to zero, with a tolerance ι of 0.5 percent (e.g. workers are considered Type-I rational if they expect a part-time wage penalty between -0.5 and 0.5 percent).

Table B.13: Belief Types based on Public Sector Employees

$\tilde{E}$ = Self-beliefs PT penalty	Public sector	Excl. civil servants	Civil servants
Type I	76.60	75.23	81.25
Type II	17.73	19.27	12.5
Type III	5.67	5.50	6.25
N	141	109	32

Notes. GSOEP-IS 2019. Cells contain shares in percent. Type I: $\tilde{E}_i \in -\iota, \iota)$, Type II: $\tilde{E}_i > \iota$, Type III: $\tilde{E}_i < -\iota$, with tolerance $\iota = 0.5$ percent.



Notes: Binned scatter with linear fit of the self-expected causal part-time penalty plotted against the perceived raw occupational wage gap between full-time and part-time workers, residualized for corrected occupation part-time wage gaps based on public sector employees. Dashed 45-degree line benchmarks full selection neglect. Occupation based on 3-digit KldB 2010. Data sources: GSOEP-IS 2019 (beliefs), VSE 2018 (raw gaps), GSOEP 2010-2019 (corrected gaps).

Figure B.9: Perceived Causal and Raw Part-Time Wage Gaps based on Public Sector Employees

B.5.8 Additional Experimental Results

Table B.14: Experimental Belief Types

$\tilde{E}$ = Self-beliefs PT penalty	Control group	Treatment 1	Treatment 2
Type I	61.89	49.82	53.98
Type II	27.62	39.64	33.04
Type III	10.49	10.55	12.98
N	286	275	339

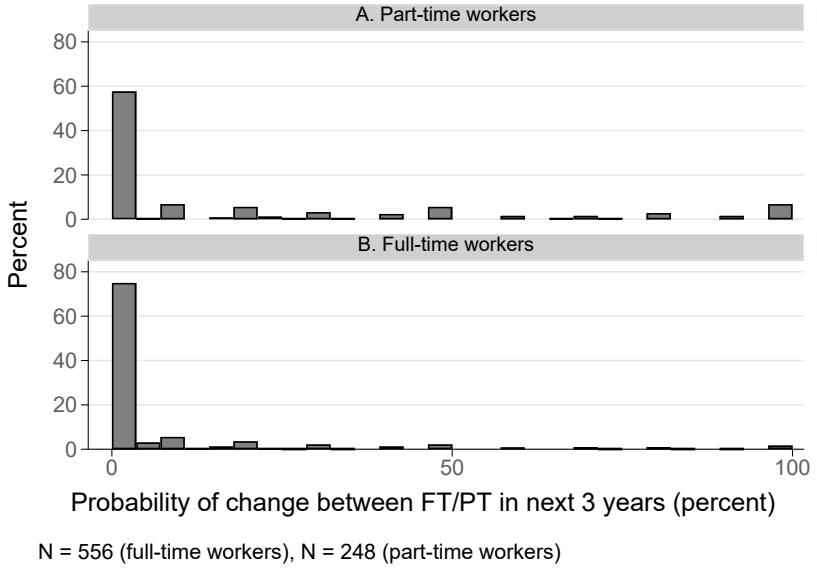
Notes. GSOEP 2019. Cells contain shares in percent. Type I: $\tilde{E}_i \in (ATT_{R_i} - \iota, ATT_{R_i} + \iota)$, Type II: $\tilde{E}_i > ATT_{R_i} + \iota$, Type III: $\tilde{E}_i < ATT_{R_i} - \iota$, with tolerance $\iota = 2$ percent and corrected occupation group part-time wage gap ATT_{R_i} based on the VSE 2018 and 3-digit occupation codes (KldB 2010).

Table B.15: Experimental Results: Heterogeneous Treatment Effects

	Correlation treatment (T1 vs. C)	Correlation inc. de-bias (T2 vs. C)	Overall treatment (Treat vs. C)	De-biasing effect (T2 vs. T1)
Full sample	3.49***	1.29	2.34**	−2.25*
Female × TE	−0.50	1.42	0.45	1.61
Full-time × TE	−0.64	−2.20	−1.30	−1.61
University × TE	0.76	−0.35	0.44	−0.88
Age > 45 × TE	−0.02	0.93	0.42	0.64
Eastern Germany × TE	−1.00	−2.41	−1.96	−1.55
Public sector × TE	−3.27	1.25	−0.71	4.32
Firm size > 200 × TE	0.32	0.28	0.35	−0.14
Temporary contract × TE	2.05	3.91	3.16	2.44
Managerial position × TE	−1.01	−2.06	−1.60	−1.06

Notes. GSOEP 2019. Dependent variable is the expected part-time penalty in percent. Cells contain coefficient estimates of subgroup indicators interacted with bivariate treatment indicators (TE) from multivariate regressions with controls for employment status (part-time/full-time), gender, education (basic/middle/university), age, region (east/west), employment sector (private/public), an indicator for firm size (>/< 200 employees) and a constant. Treat=T1+T2. Six individuals with missing values in the control variables were dropped. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.5.9 Behavioral Implications



Notes: Distribution of the subjective probability to switch from part-time to full-time (Panel A, part-time workers) and from full-time to part-time (Panel B, full-time workers) within the next 3 years. Data source: GSOEP-IS 2017-19.

Figure B.10: Planned Transition Probabilities

Table B.16: Worker Beliefs and Realized Employment Transitions

Dep.Var. = Transition in t+1 (yes/no)	FT workers		PT workers	
	(1)	(2)	(3)	(4)
Self-beliefs PT penalty	−0.001	−0.021	0.003**	0.035*
	(0.001)	(0.024)	(0.001)	(0.019)
Planned transition probability	0.001	0.013	0.004***	0.032***
	(0.001)	(0.010)	(0.001)	(0.009)
Raw PT wage gap	0.002	0.050	0.010*	0.095**
	(0.002)	(0.045)	(0.005)	(0.047)
Adjusted PT wage gap	−0.004	−0.094	−0.016**	−0.168**
	(0.003)	(0.086)	(0.008)	(0.067)
Public sector (yes/no)	−0.046	−0.978	−0.072	−1.165
	(0.042)	(1.126)	(0.048)	(0.762)
Firm size > 200 (yes/no)	0.024	0.481	0.046	1.267
	(0.027)	(0.616)	(0.043)	(0.852)
Education: medium	−0.010	−0.432	−0.045	−0.936
	(0.032)	(0.820)	(0.078)	(0.858)
Education: university	−0.017	−0.481	0.072	0.327
	(0.037)	(0.896)	(0.094)	(0.864)
Female (yes/no)	0.069**	1.491**	−0.203**	−1.670***
	(0.034)	(0.644)	(0.079)	(0.602)
Age in years	0.000	0.004	0.002	0.012
	(0.001)	(0.025)	(0.002)	(0.032)
Eastern Germany (yes/no)	0.021	0.333	−0.073	−1.326
	(0.039)	(0.617)	(0.045)	(0.877)
N	351	351	152	152
Estimation	LPM	Logistic	LPM	Logistic

Notes. GSOEP 2017-2019. Dependent variable is a binary indicator of transitioning from full-time to part-time (full-time workers) or from part-time to full-time (part-time workers) in the next year. Coefficient estimates from linear probability models (LPM) and logistic regressions. Base category for education is low education. Standard errors clustered at the person level in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C

Appendix to Chapter 3

C.1 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.

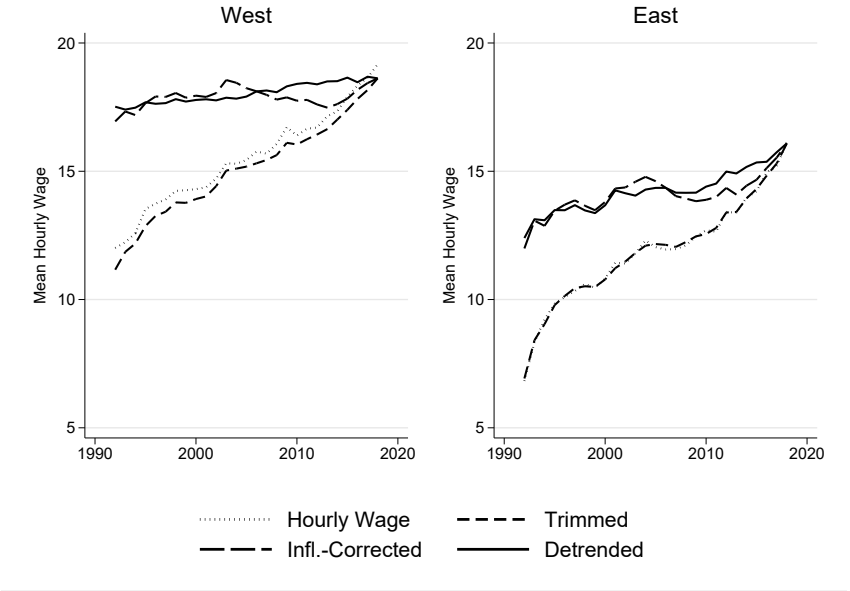
C.1.1 Variable Description

We define *employment* based on annual measures of self-reported employment status[1], which is either full-time, part-time or non-working. In the structural model, working hours for each discrete employment category are modeled using the respective sample medians of agreed contractual working hours excluding overtime: 39 hours if full-time, 21 hours if part-time and 0 if non-working. *Work experience* in part-time and full-time is measured in years and is also constructed from self-reported employment status over time, except for first-time interviewed individuals who report detailed employment histories retrospectively, including years spent in full- and part-time employment. *Hourly wages* are constructed from monthly gross labor income and agreed contractual working hours excluding overtime. We trim wages at percentiles 1 and 99 from below and above for each survey year and convert wage rates to real terms using the consumer price index and base year 2018. For the structural analyses, we eliminate real wage growth by applying the detrending procedure proposed by Blundell et al. (2016). Figure C.1 shows the impact of trimming, inflation correction and detrending on the wage evolution. Likewise, *expected hourly wages* are also constructed based on agreed contractual working hours, trimmed and converted to 2018 real terms. *Education* is defined by the highest degree obtained, aggregated to three categories based on the CASMIN[2] 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*

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

[2]Comparative Analysis of Social Mobility in Industrial Nations

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*.



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.

Figure C.1: Wage Evolution and Detrending

C.1.2 Additional Sample Restrictions in the Structural Analysis

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

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

C.1.3 Comparison of SOEP and SOEP-IS

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

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

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

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

C.2 Earnings Expectations

C.2.1 Survey Questions (Example Screenshot)

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

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

C.2.2 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.

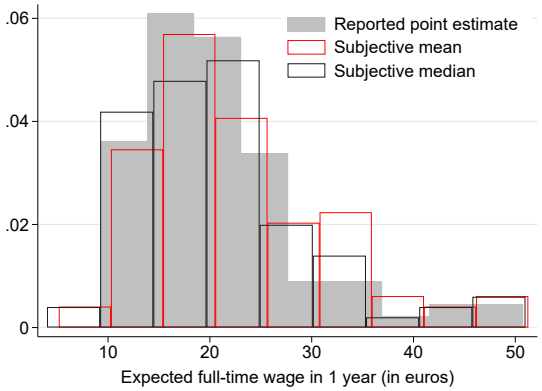
C.2.3 Robustness: Probabilistic Belief-Elicitation

In our main specification, we use reported point estimates of expected wages. In this section we present estimates of central tendency for expected wages based on the probabilistic questions from SOEP-IS wave 2018. We use reported probabilities for earning less than 80 percent and more than 120 percent of the respective point estimate and nonparametric spline interpolation to fit smooth individual-specific cumulative density functions (C.D.F.s) that pass through all reported probabilities. This approach imposes weaker assumptions than parametric fits (Bellemare et al., 2012). Specifically, we use piece-wise cubic hermite interpolating polynomials, a wage grid with a stepsize of 1 Euro, a lower bound of zero and an upper bound equal to the 99th percentile of doubled point estimates to construct individual-specific C.D.F.s.[3]

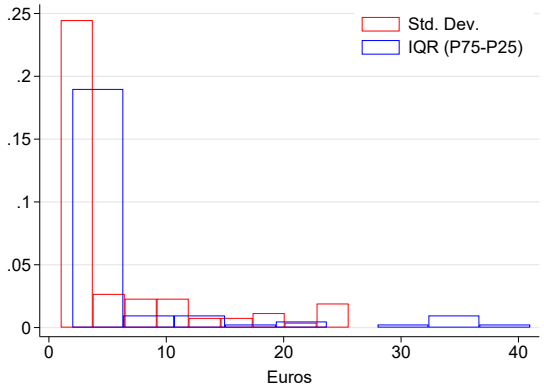
Sample means of reported point estimates and probabilistic measures of central tendency and uncertainty based on fitted C.D.F.'s are presented in Table C.2. Figures C.3 and C.4 show the corresponding distributions. Individuals assign most probability mass to values close to the point estimates, and similar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

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

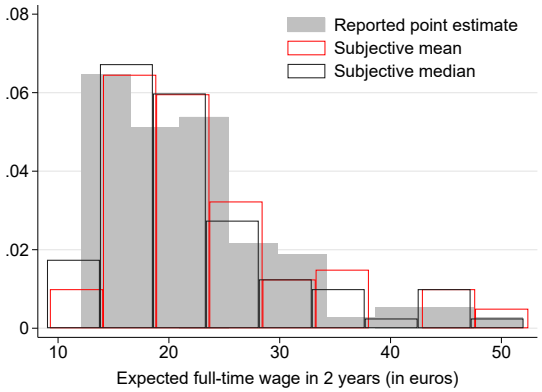
(a) **Central Tendency**
Expected Full-Time Wage in 1 Year



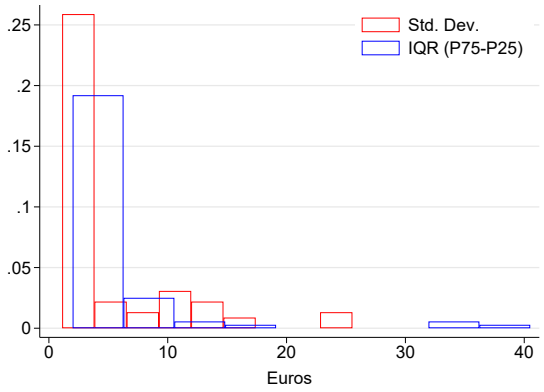
(b) **Uncertainty**
Expected Full-Time Wage in 1 Year



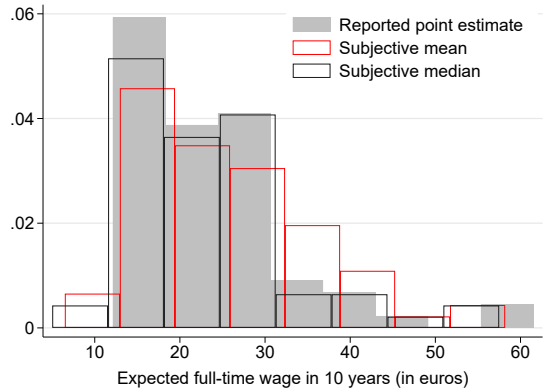
(c) **Central Tendency**
Expected Full-Time Wage in 2 Years



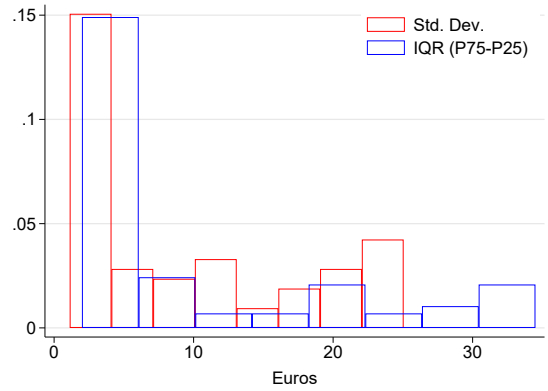
(d) **Uncertainty**
Expected Full-Time Wage in 2 Years



(e) **Central Tendency**
Expected Full-Time Wage in 10 Years



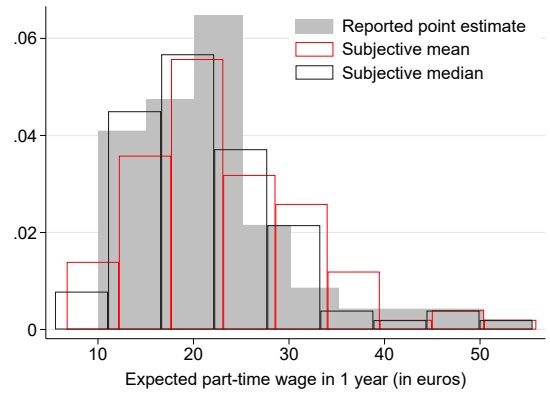
(f) **Uncertainty**
Expected Full-Time Wage in 10 Years



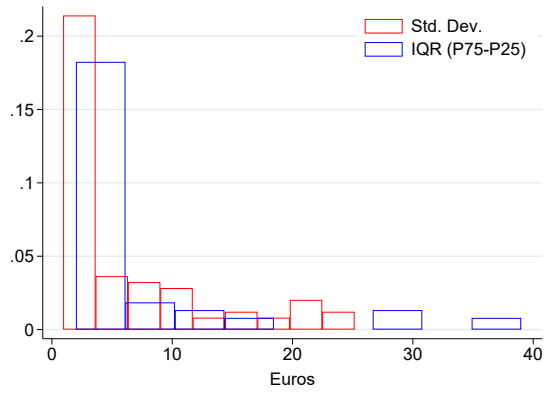
Notes: Source: SOEP-IS (2018), Own calculations.

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

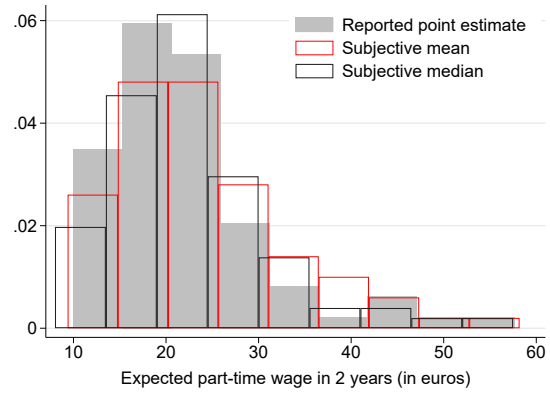
(a) **Central Tendency**
Expected Part-Time Wage in 1 Year



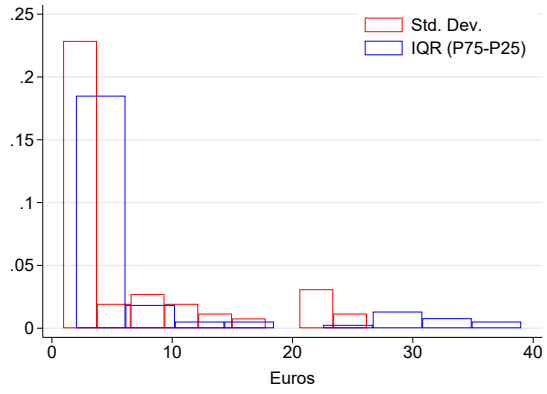
(b) **Uncertainty**
Expected Part-Time Wage in 1 Year



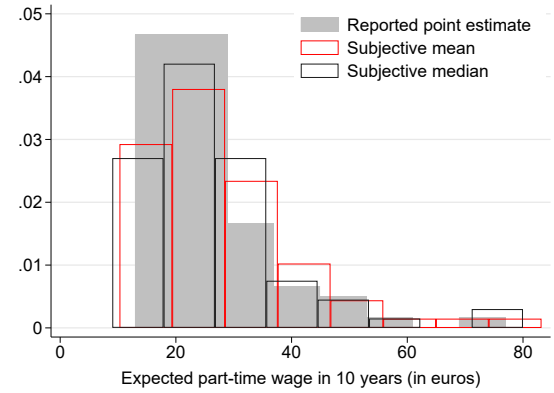
(c) **Central Tendency**
Expected Part-Time Wage in 2 Years



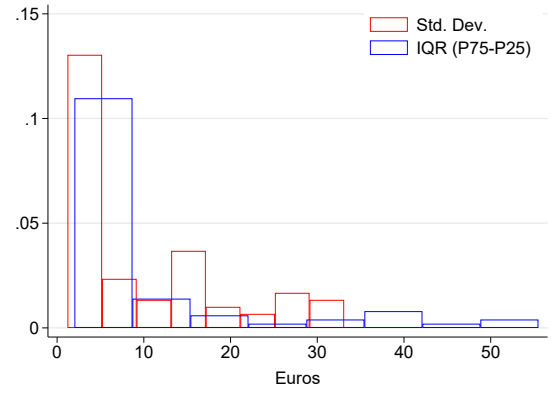
(d) **Uncertainty**
Expected Part-Time Wage in 2 Years



(e) **Central Tendency**
Expected Part-Time Wage in 10 Years



(f) **Uncertainty**
Expected Part-Time Wage in 10 Years



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

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

Table C.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.

C.2.4 Robustness: Specification with Experience in Levels

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

	Total	Low education	Medium education	High education
	(1)	(2)	(3)	(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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.2.5 Additional Results: Heterogeneity in Earnings Expectations

Table C.4: Heterogeneity in Expected Returns to Experience

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

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

C.2.6 Robustness: Specification with Real Wages

Table C.5: Sensitivity: Inflation-Adjustment

	Total	Low education	Medium education	High education
	(1)	(2)	(3)	(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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.2.7 Robustness: Belief-Elicitation based on Hourly Wage Information

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

	Total	Low education	Medium education	High education
	(1)	(2)	(3)	(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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Control Functions

In this Appendix we provide information about the first stage regressions for the control functions which we estimate separately for the three education groups. For identification we exploit variation in the tax and transfer system between the years 1992 and 2018 and simulate for all women the net household income out-of work, in part-time employment and in full-time employment. We then use different functional forms of the residualized simulated incomes[4] in the three employment states in addition to the number of children as instruments to construct the control functions.

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

C.3.1 Selection into Employment

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

Table C.7: First Stage - Employment

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

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

The instruments are highly significant for all education groups. As expected children have a negative effect on employment. In contrast, the simulated income in non employment has a positive effect on employment which is related to the variation in out

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

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.

C.3.2 Selection into Full-Time Employment

The selection process into full-time employment is explained by the number of children in different age groups and the woman's own age. In addition we construct instruments based on the residualized simulated income in part-time and in full-time employment[5]: 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. (2020) we do not find a clear pattern for the simulated income in full time employment.

C.3.3 Experience in Full-Time and Part-Time Employment

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

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

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

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

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

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

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

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

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

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

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

C.3.4 Robustness: Wage Equation

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

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

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

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

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

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

Notes: SOEP v35. All estimations include a fixed effect and an indicator for living in Eastern Germany. The control functions account for selection into employment (λ^e), selection into full-time employment (λ^h), and endogeneity of ex-

The central findings of these specification are very similar to the results of the main specification. Adding an indicator for part-time work in the current period does hardly affect the point estimates of the returns to part-time and full-time experience (Table C.11). Consistent with previous studies for Germany, see e.g. Paul (2016) or Schrenker and Zucco (2020) and other countries (Aaronson and French, 2004; Hirsch, 2005; Booth and Wood, 2008) we find that conditional on the experience terms, there exists no large contemporaneous wage penalty of working part-time.[6]

In Table C.12, we present the results of the specification with linear and quadratic terms. The realized returns to full-time experience are larger than the returns to part-time experience. Returns to part-time experience are either not significant or very small in magnitude. An F-test on the equality of the returns to full- and part-time experience is rejected for all education groups.[7] Thus the central finding of a part-time experience penalty does not depend on the functional form of the wage equation.

C.4 Initial Conditions and Exogenous Processes

C.4.1 Initial Conditions

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

C.4.2 Marriage, Divorce and Partner Earnings

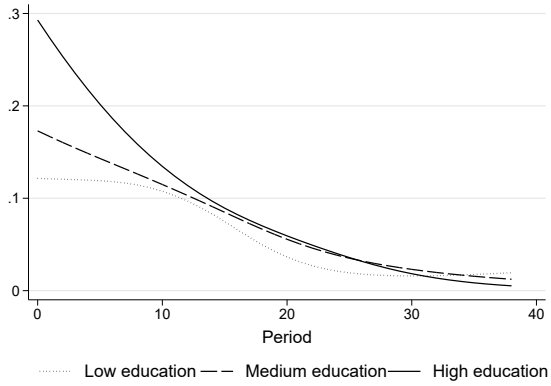
For women aged 22-60, we estimate the probability that a single woman finds a partner in a given year separately by education (low, medium or high) using logistic regressions with a cubic polynomial in female age. Analogously, we estimate the probability that a woman who had a partner in the previous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

C.4.3 Fertility

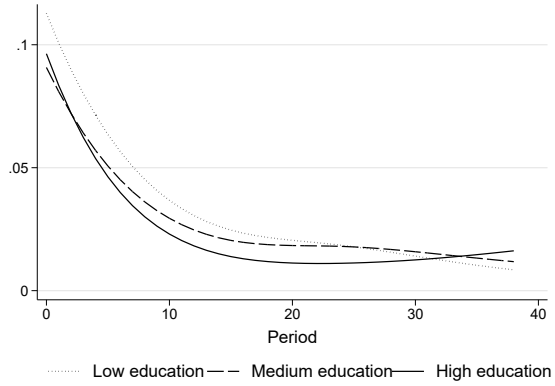
To estimate annual birth probabilities we estimate education-specific logistic regressions of child birth as a function of female age up to a third order polynomial for women in child-bearing age until age 42. We set birth probabilities to zero for women above age 42.

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

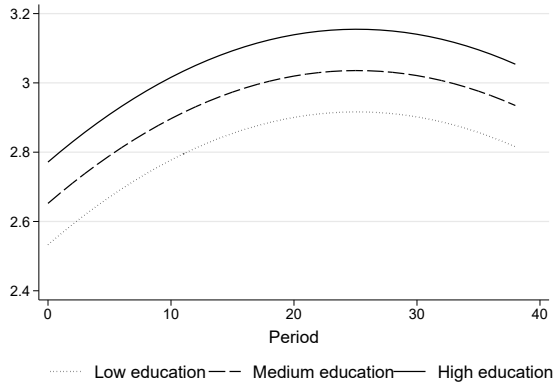
[7] Specifically, we test the joint equality of the linear and the quadratic experience coefficients.



(a) Partner Arrival



(b) Partner Separation



(c) Partner Log Wage

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

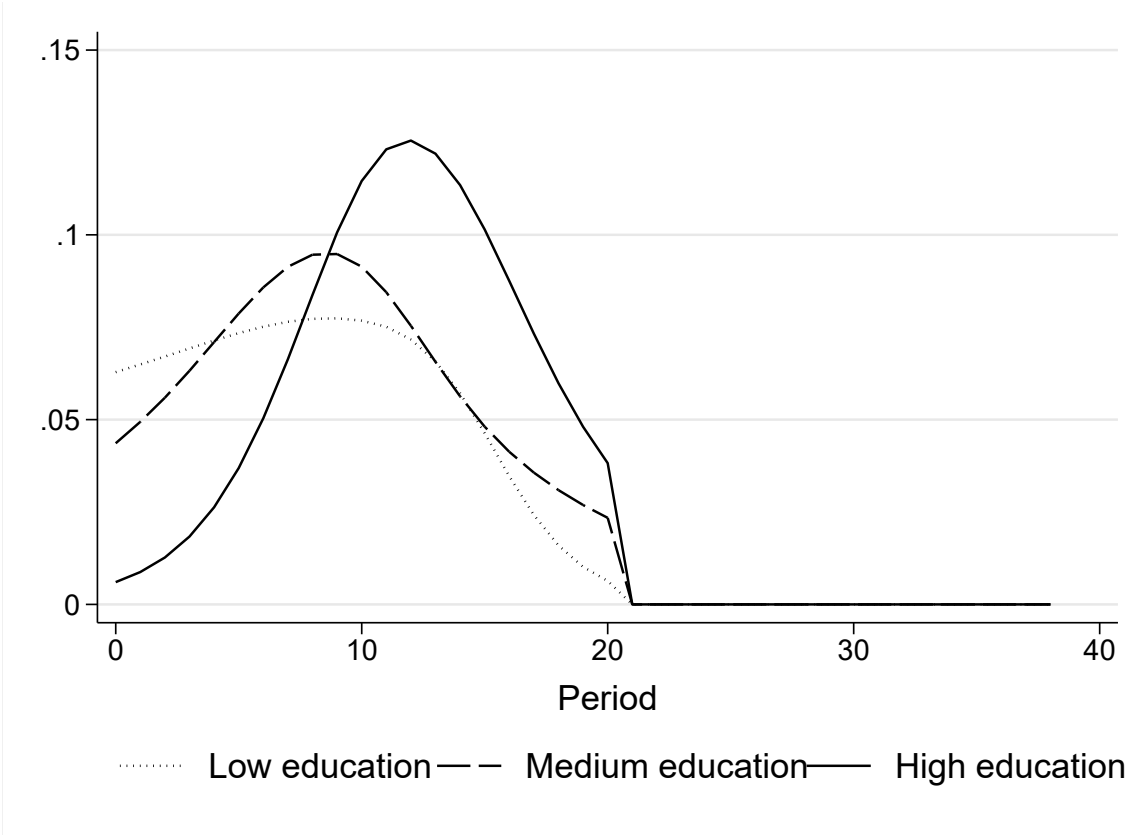


Figure C.6: Annual Birth Probabilities

C.5 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 3.5.2). For the estimation of the structural model we focus on the period 2007-2018. During that time period the general structural of the tax and transfer system was only slightly changed.

Social Security Contribution and Income Taxation

Individuals pay social security contributions for health, unemployment and pension benefits. The social security tax, including contributions for health benefits, unemployment benefits, and pension benefits is a flat rate tax of 21,5% on individuals labor earnings below a cap of 63,000 euros per year.[8]

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.[9] Income tax is based on taxable household income, which in our model is equal to the taxable labor earnings all household members minus the household's tax-deductible social security contributions. Individual earnings in excess of 7,664 euros per year are taxable. Social security contributions can be deducted from taxable income. The solidarity surcharge (Solidaritaetszuschlag) is included in income tax and is equal to 5.5% of the household's tax liability, excluding social security contributions.

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

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

$$\widetilde{\text{SA}}_{i,j,t} = \max\{\text{SAFloor}_{i,j,t} - \widetilde{y}_{i,j,t}, 0\}, \tag{C.1}$$

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

The social assistance income floor can be written as:

$$\text{SAFloor}_{i,j,t} = G \times E_{i,j,t}. \tag{C.2}$$

[8] 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.

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

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

The social assistance income floor $\text{SAFloor}_{i,t}$ varies between household types. For singles, it is equal to 91 euros per week, a household receives in addition 82 euros for an adult partner and 59 euro for children . In addition households receive housing benefits which amount to 77.5 per week for a single and increase with the number of other household members by about 15 Euros per week.[11]

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.[12]

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.[13]. The parents' benefit is not means-tested on household income and the amount of the benefit depends on earnings prior to birth. It replaces 67% of previous net earnings, but does not exceed 1800 euro per month and there is a floor of 300 Euro per months. We approximate the parents' benefit with 67 of potential net full time earnings.[14]

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

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

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

[13]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

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

Appendix D

Appendix to Chapter 4

D.1 Research Design

D.1.1 ISCO Major Groups and Skill Levels

Table D.1: ISCO-88 Major Occupational Groups and Skill Levels

No.	Major Occupational Group	Skill Level
1	Managers	3 + 4
2	Professionals	4
3	Technicians and Associate Professionals	3
4	Clerical Support Workers	2
5	Services and Sales Workers	2
6	Skilled Agriculture, Forestry, and Fishery Workers	2
7	Craft and Related Trades Workers	2
8	Plant and Machine Operators, and Assemblers	2
9	Elementary Occupations	1
0	Armed Forces Occupations	1 + 2 + 4

D.1.2 Event Study Design

This Section presents the event study design described in Section 4.4.3 using formal notation.

We estimate the following event study model,

$$Y_{ict} = \alpha + \sum_{k=2002}^{2013} \beta_k \Delta ETR_c \times \mathbb{1}[t = k] + \gamma_c + \gamma_t + X'_{ict}\Gamma + \epsilon_{ict} \tag{D.1}$$

where $\mathbb{1}[t = k]$ is an indicator that is equal to 1 if the time period is equal to k and zero otherwise. γ_c and γ_t are cohort and year fixed effects. In some specifications, industry and age group fixed effects are also included.

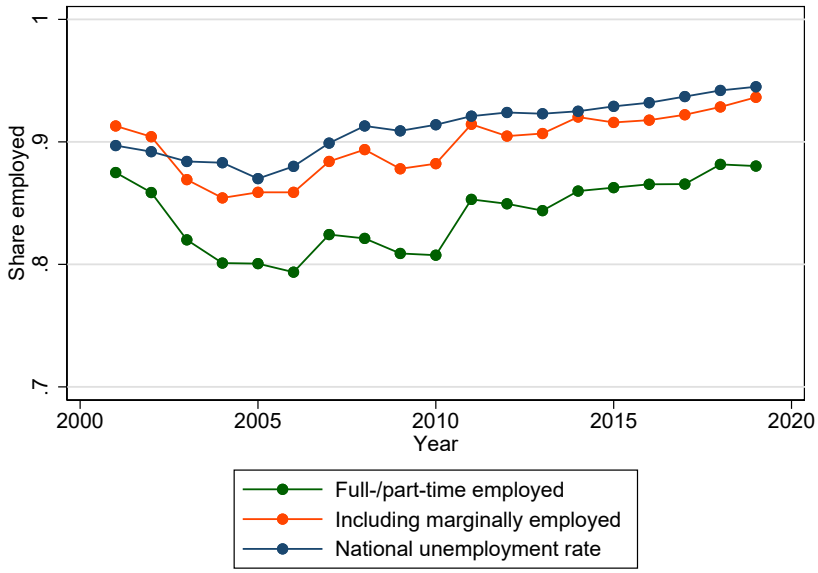
To account for different pre-trends in hourly wage growth, we also estimate a version of the event study model including pre-treatment differences obtained from regressing the pre-reform outcome variable on the year including individual level controls (Dustmann et al., 2022),

$$Y_{ict} = \alpha + \sum_{k=1}^{3} \mathbb{1}[b_{k-1} < c \leq b_k]\delta_{tc} + \sum_{k=2002}^{2013} \beta_k \Delta ETR_c \times \mathbb{1}[t = k] + \gamma_c + \gamma_t + X'_{ict}\Gamma + \epsilon_{ict} \quad \text{(D.2)}$$

where $b_0 = 1952$, $b_1 = 1956$, $b_2 = 1960$ and $b_3 = 1964$. $\mathbb{1}[b_{k-1} < c \leq b_k]$ is equal to 1 if an individual is born between b_{k-1} and b_k, and δ_{tc} gives the mean wage growth in the time period 2002 to 2007 within cohort-groups conditional on individual level controls.

D.2 Additional Results

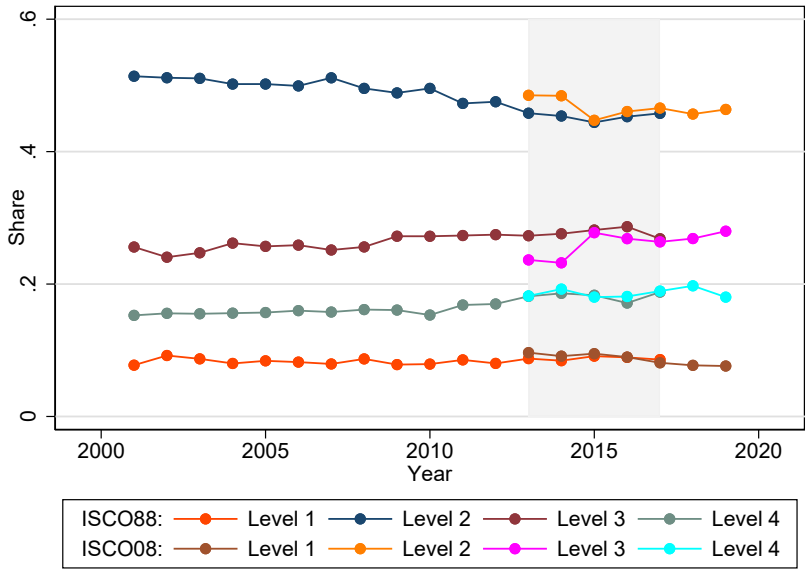
D.2.1 Employment over Time



Notes: The plot shows the proportion of workers aged 40 to 60 in employment in the SOEP sample, as well as the national unemployment rate for non self-employed individuals. Data Source: SOEP v36, 2000-2019 (employment ratios), Bundesagentur für Arbeit (national unemployment rate).

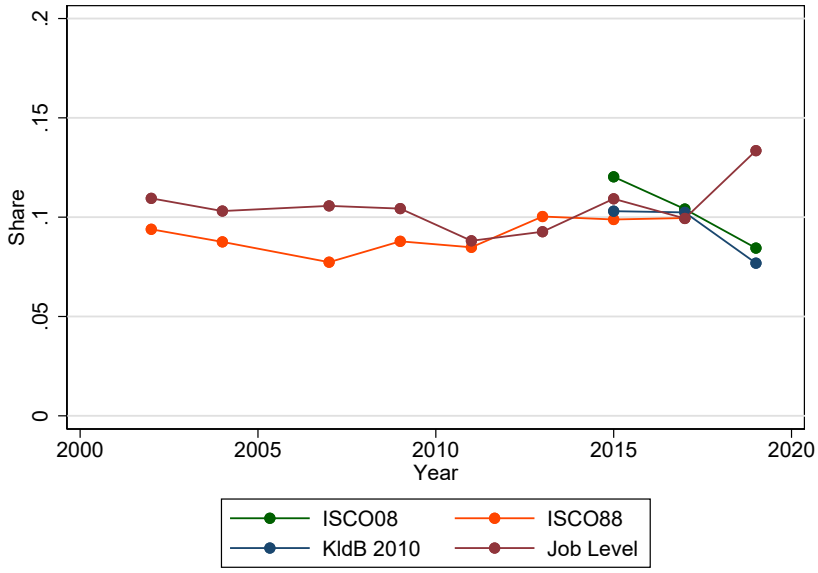
Figure D.1: Employment Ratios

D.2.2 Skills and Promotions over Time



Notes: The plot shows the proportion of workers in different skill levels according to the ISCO-88 and ISCO-08 classifications. Estimates are based on employed workers born between 1953-1964 who are below the age of 60. Data Source: SOEP v36, 2000-2019.

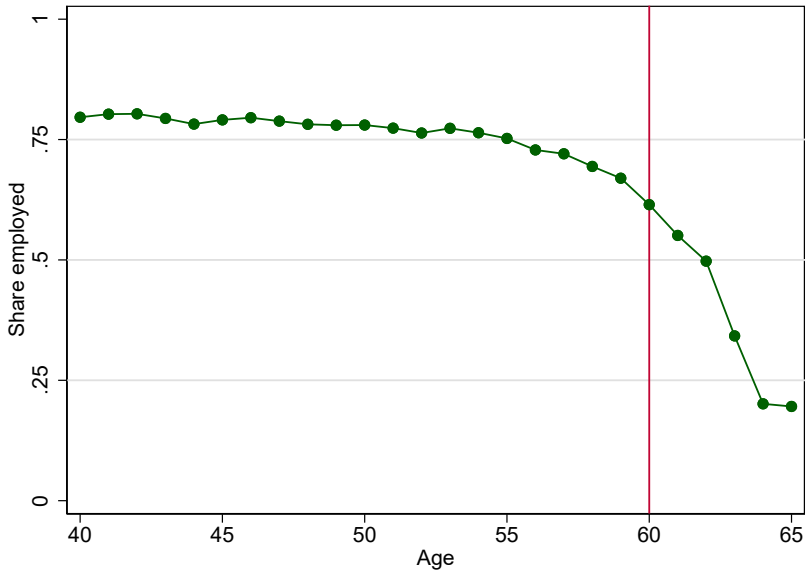
Figure D.2: Shares of ISCO Skill Levels over Time



Notes: The plot shows the proportion of workers who were promoted since the last observation period. Promotions are measured based on the skill level of the occupational position according to the ISCO-88 or the ISCO-08 classification, the German classification of occupations (KldB-2010) or the job level. The sample includes employed workers born between 1953-1964 who are below the age of 60. Data Source: SOEP v36, 2000-2019.

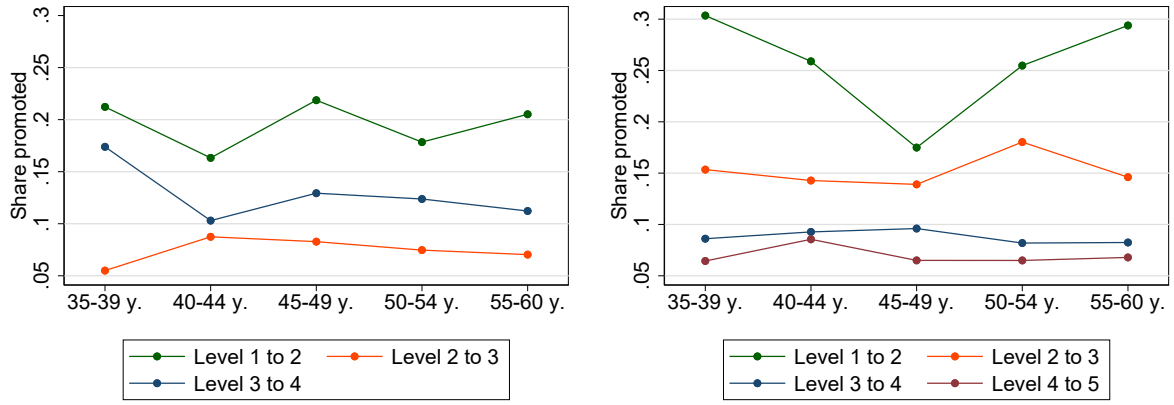
Figure D.3: Share of Promotions over Time

D.2.3 Employment, Promotions and Wage Growth over Age



Notes: The plot shows the share of individuals that work either part-time or full-time by age. Estimates are based on individuals born between 1953-1964, excluding individuals that are not in the labor market. Data Source: SOEP v36, 2000-2017.

Figure D.4: Share of Employed Individuals over Age

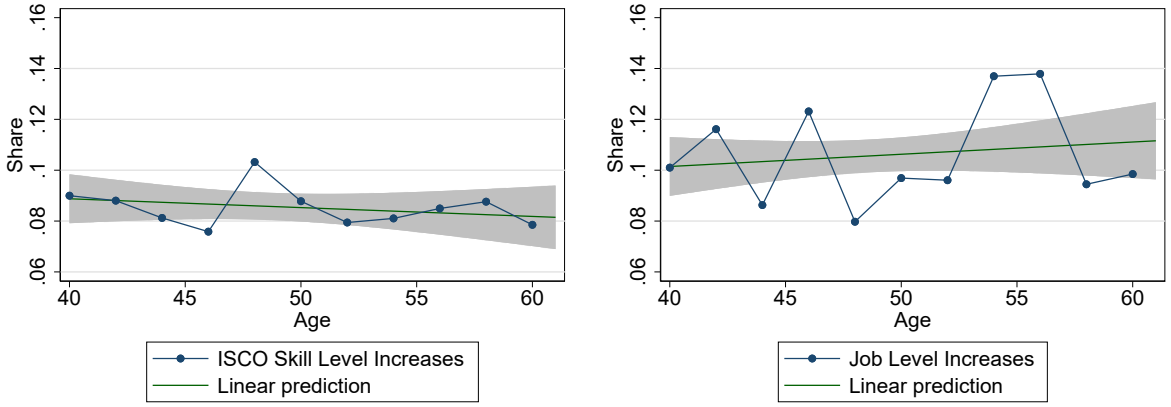


(a) ISCO Skill Level Increases

(b) Job Level Increases

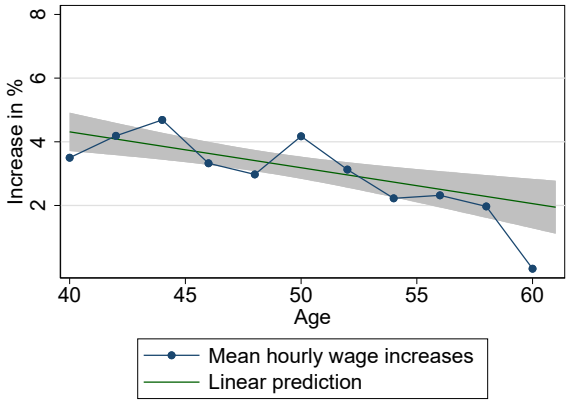
Notes: The plots show the proportion of workers who were promoted to a higher occupational position relative to the previous observation period by level of the current job over the life-course, based on ISCO skill levels (panel a) or job levels (panel b). The sample includes employed individuals between 35 and 60 years born between 1944 and 1966. Data Source: SOEP v36, 2000-2017.

Figure D.5: Promotions Probability by Age per Level



(a) ISCO Skill Level Increases

(b) Job Level Increases



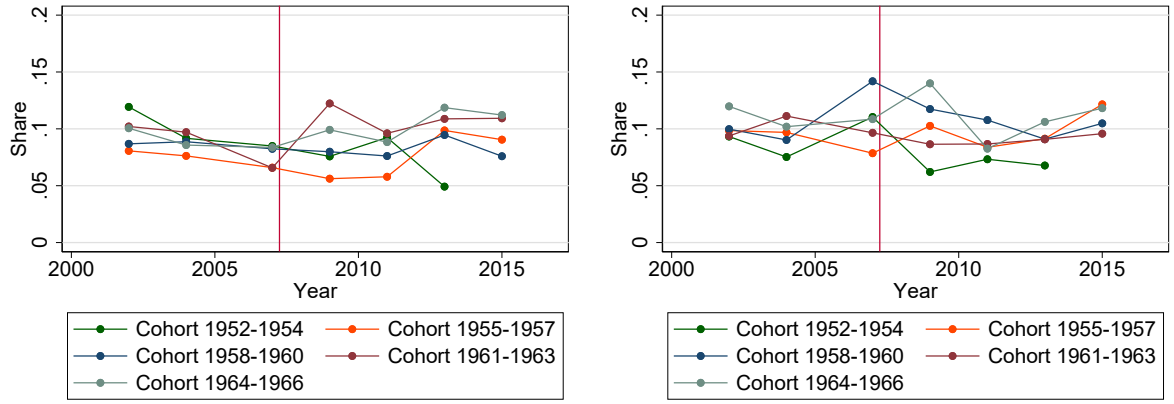
(c) Hourly Wage Increases

Notes: The plots show the proportion of workers who were promoted since the last observation period (panel a,b) and the hourly wage increase over the last year (panel c) with linear fitted trends in the pre-reform period by age. The sample includes employed individuals between 40 and 60 years born between 1944 and 1966. Data Source: SOEP v36, 2001-2007.

Figure D.6: Promotions and Wage Increases over Age Pre-Reform

D.2.4 Supporting Evidence of the Identifying Assumptions

Figure D.7 depicts the pre- and post-reform trends in the key outcome variables based on a finer differentiation into cohort groups relative to the definition in Figure 4.3. The overall picture remains the same, but the graphs are a little less clear due to smaller samples. In Table D.2, we show pre-reform sample means for key socio-demographic and occupational characteristics for each cohort, based on the larger SIAB data, showing that adjacent cohorts are very similar in terms of key characteristics prior to the reform.



(a) ISCO Skill Level Increases

(b) Job Level Increases

Notes: The plots show the proportion of workers who were promoted since the last observation period for different birth cohorts, with promotions based on the ISCO-88 skill level (panel a) or the occupational job level (panel b). The vertical red line markes the time of the 2007 reform. The sample includes employed workers born between 1952-1966 who are below the age of 60. Data Source: SOEP v36, 2000-2019.

Figure D.7: Parallel Trends for Cohort Groups

Table D.2: Pre-Reform Characteristics by Cohort

	1953	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964
Female	46.8%	47.2%	46.8%	46.7%	47.0%	46.6%	46.4%	45.7%	45.3%	44.7%	44.4%	44.0%
German citizenship	95.7%	95.2%	95.0%	95.2%	95.3%	95.3%	95.4%	94.8%	95.2%	94.7%	94.4%	94.3%
East German	23.0%	21.8%	21.2%	20.5%	19.4%	19.4%	20.6%	20.0%	19.1%	19.9%	19.9%	19.3%
Education												
No vocational training	8.0%	7.7%	7.9%	7.5%	7.4%	7.6%	7.4%	7.6%	7.1%	7.3%	6.8%	6.6%
Vocational training	77.4%	77.3%	77.2%	77.6%	78.3%	78.0%	78.5%	77.7%	78.5%	77.1%	77.6%	77.8%
University or university of applied science	14.6%	15.0%	14.9%	14.9%	14.3%	14.3%	14.1%	14.7%	14.5%	15.5%	15.5%	15.6%
Gross real daily wage, imputed (in Euros)	108.11	108.15	108.70	108.90	108.18	108.48	106.99	107.60	108.30	108.55	108.34	108.50
Yearly labor income (in Euros)	38,897	38,931	39,166	39,268	39,033	39,202	38,608	38,809	39,060	39,129	39,035	39,067
Days employed, this calender year	356.7	356.7	356.9	357.1	356.8	357.2	356.8	356.7	356.5	356.2	356.2	356.1
Days benefit recipience, this calendar year	4.7	4.7	4.6	4.4	4.7	4.1	4.3	4.4	4.5	4.7	4.3	4.5
Work experience (in years)	20.9	20.7	20.4	20.2	19.8	19.3	18.6	17.8	17.2	16.5	15.9	15.3
UI benefits receipt (in years)	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Tenure at the firm (in years)	10.9	10.8	10.5	10.3	10.0	9.6	9.4	8.9	8.7	8.4	8.1	8.0
Part-time	20.8%	20.9%	21.5%	21.3%	21.4%	21.4%	21.9%	21.3%	20.8%	20.8%	20.7%	20.3%
Occupational skill level												
Level 1	6.9%	6.7%	6.3%	6.6%	6.3%	6.1%	6.1%	6.1%	6.1%	5.4%	5.1%	5.0%
Level 2	72.4%	71.7%	72.3%	72.0%	72.9%	72.8%	73.1%	72.6%	72.8%	72.9%	73.4%	73.3%
Level 3	8.9%	9.4%	9.3%	9.2%	8.7%	8.8%	8.8%	8.8%	8.8%	9.1%	8.9%	8.7%
Level 4	11.8%	12.2%	12.1%	12.2%	12.0%	12.4%	12.0%	12.5%	12.4%	12.6%	12.6%	13.0%
Promotions												
Overall promotions	1.01%	0.97%	1.03%	1.06%	1.04%	1.10%	1.03%	1.13%	1.29%	1.36%	1.34%	1.41%
W/in firm promotions	0.10%	0.10%	0.11%	0.14%	0.10%	0.07%	0.11%	0.13%	0.11%	0.13%	0.10%	0.09%
W/in job group promotions	0.16%	0.16%	0.15%	0.16%	0.16%	0.19%	0.15%	0.16%	0.21%	0.20%	0.18%	0.17%
W/in firm and job group promotions	0.03%	0.02%	0.02%	0.03%	0.02%	0.00%	0.01%	0.02%	0.02%	0.01%	0.02%	0.01%
Observations	23,075	24,078	24,907	26,142	27,520	27,586	29,951	30,451	32,014	32,269	33,967	33,371

Notes: SIAB (2005-2006). The Table shows pre-reform sample means in key demographic and occupational characteristics by cohort for employed individuals born between 1953 and 1964. Occupational skill levels and promotion rates based on the German Classification of Occupation (KldB) 2010.

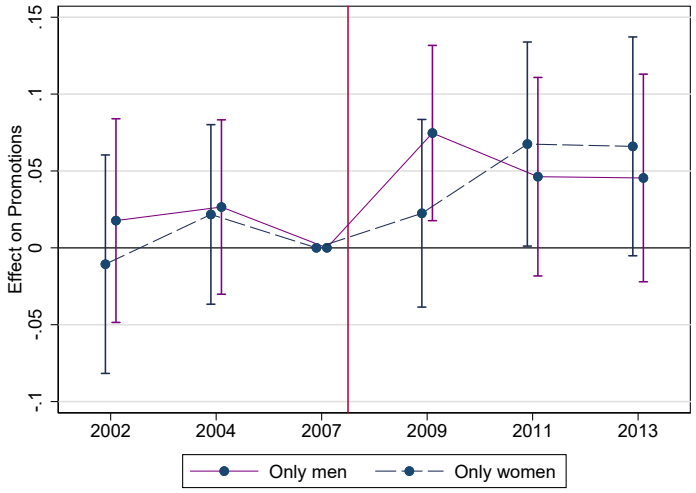
D.2.5 Event Study Estimates

Table D.3: Event Study Effects

	Wage Increases	Promotions	
	(1)	(2)	(3)
Pre-reform			
$\Delta ETR \times 2001$	-0.012		
	(0.030)		
$\Delta ETR \times 2002$	0.027	0.012	-0.003
	(0.028)	(0.025)	(0.028)
$\Delta ETR \times 2003$	-0.014		
	(0.028)		
$\Delta ETR \times 2004$	-0.001	0.026	0.015
	(0.025)	(0.021)	(0.023)
$\Delta ETR \times 2005$	0.011		
	(0.023)		
$\Delta ETR \times 2006$	-0.021		
	(0.029)		
$\Delta ETR \times 2007$	0	0	0
$\Delta ETR \times 2008$	0.007		
	(0.034)		
Post-reform			
$\Delta ETR \times 2009$	-0.017	0.050**	0.035
	(0.046)	(0.021)	(0.023)
$\Delta ETR \times 2010$	0.025		
	(0.036)		
$\Delta ETR \times 2011$	0.013	0.059**	0.023
	(0.032)	(0.024)	(0.026)
$\Delta ETR \times 2012$	0.026		
	(0.031)		
$\Delta ETR \times 2013$	0.024	0.057**	0.037
	(0.029)	(0.025)	(0.027)
Pre-reform mean	0.048	0.09	0.098
Observations	30,784	13,347	11,081
Time FE	Y	Y	Y
Age group FE	Y	Y	Y
Industry FE	Y	Y	Y
Diff. pre-trends	Y	N	N

Notes: SOEP v36 (2000-2013). Promotion and wage effects for employed individuals of birth cohorts 1953-1964. Column 1 gives effects for hourly wage increases, column 2 for ISCO skill increases and column 3 for job level increases. Controls include gender, migration background, region (East/West), college education, experience, experience squared, company size, and sector (public/private). Column 1 controls for different pre-trends. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01.

D.2.6 Subgroup Analyses



Notes: The plot shows event study estimates with 95 percent confidence intervals of an increase in the ETR on promotions using ISCO-88 skill levels over time, separately for men and women. The vertical red line indicates the time of the 2007 reform. Estimates based on employed individuals born between 1953-1964. Data Source: SOEP v36, 2000-2013.

Figure D.8: Promotion Effects by Gender

Table D.4: Promotion Effects by Demographic Characteristics: Job Level

	Job Level Increases		
	(1)	(2)	(3)
Post-reform $\times\Delta ETR$	0.024	0.038*	0.043**
	(0.024)	(0.021)	(0.021)
Post-reform $\times$			
Gender (1 = male)	-0.024		
	(0.018)		
Post-reform $\times\Delta ETR$			
$\times$ Gender	0.024		
	(0.023)		
Post-reform $\times$			
East Germany		0.002	
		(0.020)	
Post-reform $\times\Delta ETR$			
$\times$ East Germany		-0.005	
		(0.026)	
Post-reform $\times$			
Mig. Backgr.			0.052*
			(0.030)
Post-reform $\times\Delta ETR$			
$\times$ Mig. Backgr.			-0.054
			(0.038)
Pre-reform mean	0.098	0.098	0.098
Observations	11,081	11,081	11,081
Age FE	Y	Y	Y
Industry FE	Y	Y	Y

Notes: SOEP v36 (2000-2013). Promotion effects using job levels for employed individuals of birth cohorts 1953-1964. Including triple interaction terms for gender (column 1), East Germany (column 2) and migration background (column 3). Controls include gender, migration background, region (East/West), college education, experience, experience squared, company size, and sector (public/private). Age and industry fixed effects are included. Standard errors clustered at the individual level. * $p < .1$ ** $p < .05$ *** $p < 0.01$.

Table D.5: Promotion Effects By Socio-Economic Characteristics: Job Level

	Job Level Increases		
	(1)	(2)	(3)
Post-reform $\times\Delta ETR$	0.054**	0.011	0.040*
	(0.026)	(0.032)	(0.024)
Post-reform $\times$			
Education (1 = No college)	0.030*		
	(0.018)		
Post-reform $\times\Delta ETR$			
$\times$ Education	-0.025		
	(0.024)		
Post-reform $\times$			
High 2007 Labor Inc.		-0.023	
		(0.023)	
Post-reform $\times\Delta ETR$			
$\times$ High 2007 Labor Inc.		0.017	
		(0.029)	
Post-reform $\times$			
Large Company			0.022
			(0.018)
Post-reform $\times\Delta ETR$			
$\times$ Large Company			-0.006
			(0.023)
Pre-reform mean	0.098	0.097	0.098
Observations	11,081	9,232	11,081
Age FE	Y	Y	Y
Industry FE	Y	Y	Y

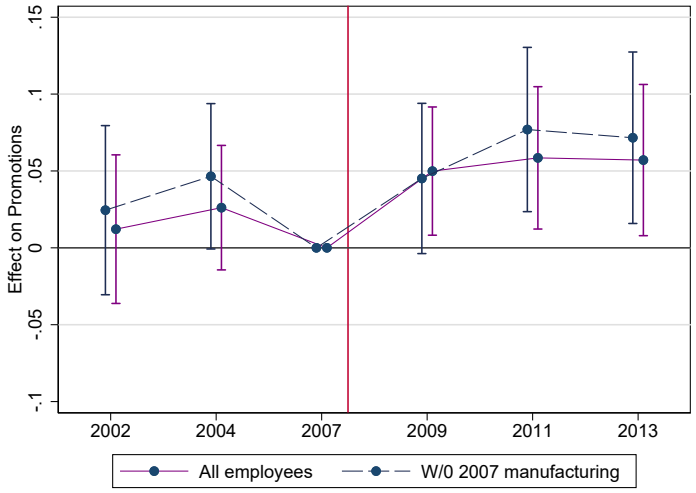
Notes: SOEP v36 (2000-2013). Promotion effects using job levels for employed individuals of birth cohorts 1953-1964. Including triple interaction terms for full-time (column 1), company changers (column 2) and company size (column 3). Controls include gender, migration background, region (East/West), college education dummy, experience, experience squared, company size, and sector (public/private). Age and industry fixed effects are included. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01.

Table D.6: Stated Reasons for Company Changes

Employer-initiated	22.23 %
Employee-initiated	28.31 %
Unclear or both-sided	11.56 %
Unknown	37.90 %

Notes: SOEP v36 (2000-2013). Reasons for a company change that are attributable to the employer include termination by the employer and closure of the company. Reasons attributable to the employee include termination by the employee, maternity/parental leave, and the dissolution of the own business. Unclear or both-sided initiatives include an amicable dissolution contract, the end of an apprenticeship, a fixed-term contract, or a leave of absence.

D.2.7 Sensitivity: Excluding the Manufacturing Sector



Notes: The plot shows event study estimates with 95 percent confidence intervals of an increase in the ETR on promotions using ISCO-88 skill levels over time, for all employees and excluding employees formerly working in the manufacturing sector. The vertical red line marks the time of the 2007 reform. Estimates based on employed individuals born between 1953-1964. Data Source: SOEP v36, 2000-2013.

Figure D.9: Promotion Effects Excluding Manufacturing

D.2.8 Sensitivity: Increasing the Time Horizon

Table D.7: Pooled Promotion Effects Until 2015

	Skill level increases			Job level increases		
	(1)	(2)	(3)	(4)	(5)	(6)
Increase in ETR × 2008-2015	0.029***	0.053***	0.051***	0.032***	0.037**	0.017
	(0.010)	(0.016)	(0.019)	(0.011)	(0.018)	(0.021)
Pre-reform mean	0.09	0.09	0.09	0.098	0.098	0.097
Observations	15,346	15,346	12,143	12,668	12,668	9,702
Age FE	N	Y	Y	N	Y	Y
Industry FE	N	Y	Y	N	Y	Y
W/o manufacturing	N	N	Y	N	N	Y

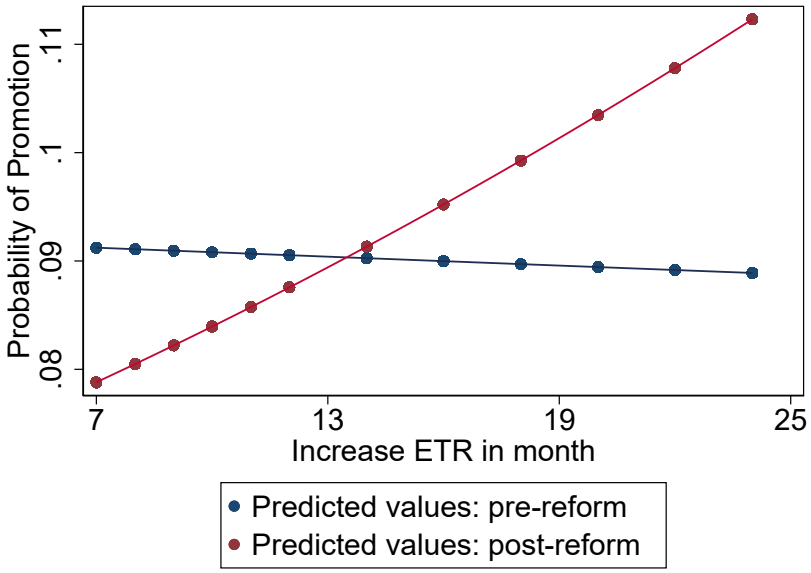
Notes: SOEP v36 (2000-2015). Promotion effects for employed individuals of birth cohorts 1953-1964, no older than 60 years. The outcome variable is promotions using skill levels in columns 1 to 3 and promotions using job levels in columns 4 to 6. Controls include gender, migration background, region (East/West), college education, experience, experience squared, company size, and sector (public/private). In columns 3 and 6, individuals who worked in manufacturing in 2007 are excluded. Standard errors clustered at the individual level. * $p < .1$ ** $p < .05$ *** $p < 0.01$.

Table D.8: Pooled Wage Effects Until 2015

	Wage Increases		
	(1)	(2)	(3)
Increase in ETR × 2008-2015	0.032*	0.041**	0.027***
	(0.017)	(0.017)	(0.008)
Pre-reform mean	0.048	0.048	0.035
Observations	36,761	36,761	36,761
Age FE	Y	Y	Y
Different pre-trends	N	Y	N
Winsorized data	N	N	Y

Notes: SOEP v36 (2000-2015). Wage effects for employed individuals of birth cohorts 1953-1964, no older than 60 years. The outcome variable is hourly wage increases. Controls include gender, migration background, region (East/West), college education, experience, experience squared, company size, and sector (public/private). In column 2 differing pre-trends are included. In column 3, the outcome variable is winsorized at the 5% level. Standard errors clustered at the individual level. * $p < .1$ ** $p < .05$ *** $p < 0.01$.

D.2.9 Sensitivity: Logistic Model



Notes: The plot shows predicted values for the probability of promotion using ISCO skill levels over the future increase in the ETR obtained from univariate logistic regression. The sample includes employed individuals born between 1953-1964. Data Source: SOEP v36, 2000-2013.

Figure D.10: Univariate Logistic Regression

Table D.9: Promotion Effects Using Logistic Regression

ISCO Skill Level Increases	(1)	(2)
Increase in ETR ×		
Post-reform	0.293***	0.570***
	(0.111)	(0.126)
Post-reform	-0.158*	-0.139
	(0.082)	(0.180)
Male		-0.020
		(0.064)
Migration background		-0.145
		(0.130)
East Germany		-0.065
		(0.100)
No college		0.238***
		(0.058)
Work experience		-0.027
		(0.022)
Squared work experience		0.000
		(0.000)
Large company (>200 employees)		0.061
		(0.056)
Public sector		-0.143*
		(0.081)
Observations	13,435	13,347
Age & industry FE	N	Y

Notes: SOEP v36 (2000-2013). Promotion effects for employed individuals of birth cohorts 1953-1964. The outcome variable is promotions using skill levels. Column 1 shows bivariate results from logistic regression. Column 2 shows effects with a full set of controls, as well as age and industry fixed effects. Robust standard errors in parentheses. * p < .1 ** p < .05 *** p < 0.01.

D.2.10 Sensitivity: Sorting into Employment

Table D.10: Promotion Effects Conditional on Pre-Reform (2006) Employment

	Skill level increases			Job level increases		
	(1)	(2)	(3)	(4)	(5)	(6)
Increase in ETR × 2008-2013	0.020	0.034*	0.035	0.021	0.014	-0.009
	(0.012)	(0.020)	(0.023)	(0.013)	(0.022)	(0.026)
Pre-reform mean	0.086	0.086	0.084	0.094	0.094	0.092
Observations	10,577	10,577	7,500	8,893	8,893	6,024
Age FE	N	Y	Y	N	Y	Y
Industry FE	N	Y	Y	N	Y	Y
W/o manufacturing	N	N	Y	N	N	Y

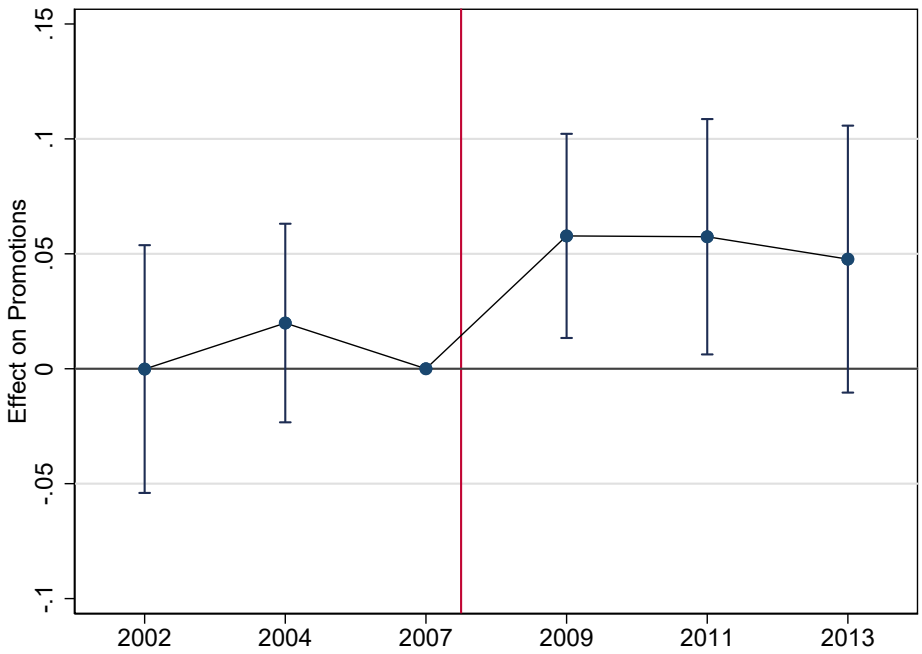
Notes: SOEP v36 (2000-2013). Promotion effects for employed individuals of birth cohorts 1953-1964, conditional on pre-reform (2006) employment. DiD estimates with controls for gender, migration background, region (East/West), college education, experience, experience squared, company size, and sector (public/private). In columns 3 and 6, individuals who worked in manufacturing in 2007 are excluded. Standard errors clustered at the individual level. * p < .1 ** p < .05 *** p < 0.01.

D.2.11 Sensitivity: Individual Fixed Effects

Table D.11: Promotion Effects with Individual Fixed Effects

	Skill level increases			Job level increases		
	(1)	(2)	(3)	(4)	(5)	(6)
Increase in ETR × 2008-2013	0.030**	0.046**	0.058**	0.029*	0.028	0.012
	(0.014)	(0.020)	(0.024)	(0.016)	(0.023)	(0.027)
Pre-reform mean	0.09	0.09	0.09	0.097	0.097	0.097
Observations	11,800	11,800	8,630	9,673	9,673	6,750
Age FE	N	Y	Y	N	Y	Y
Industry FE	N	Y	Y	N	Y	Y
W/o manufacturing	N	N	Y	N	N	Y

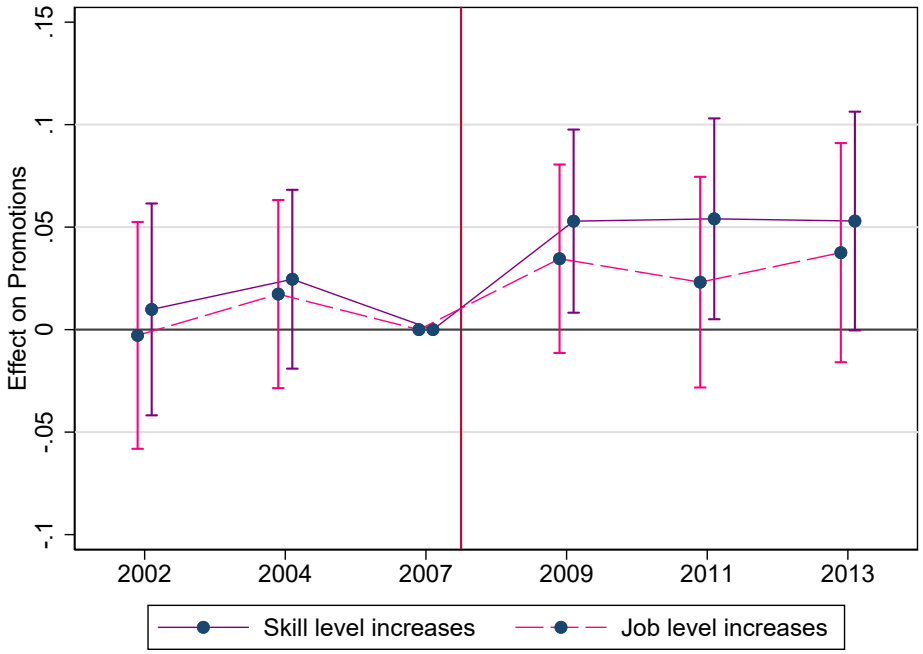
Notes: SOEP v36 (2000-2013). Promotion effects for employed individuals of birth cohorts 1953-1964. DiD estimates with controls for region (East/West), college education, experience, experience squared, company size, and sector (public/private). In columns 3 and 6, individuals who worked in manufacturing in 2007 are excluded. Standard errors clustered at the individual level. * p < .1 ** p <.



Notes: The plot shows event study estimates with 95 percent confidence intervals of an increase in the ETR on promotions using ISCO-88 skill levels over time. Regressions include individual fixed effects, as well as age group and period fixed effects. The vertical red line marks the time of the 2007 reform. Estimates based on employed individuals born between 1953-1964. Data Source: SOEP v36, 2000-2013.

Figure D.11: Promotion Effects with Individual Fixed Effects

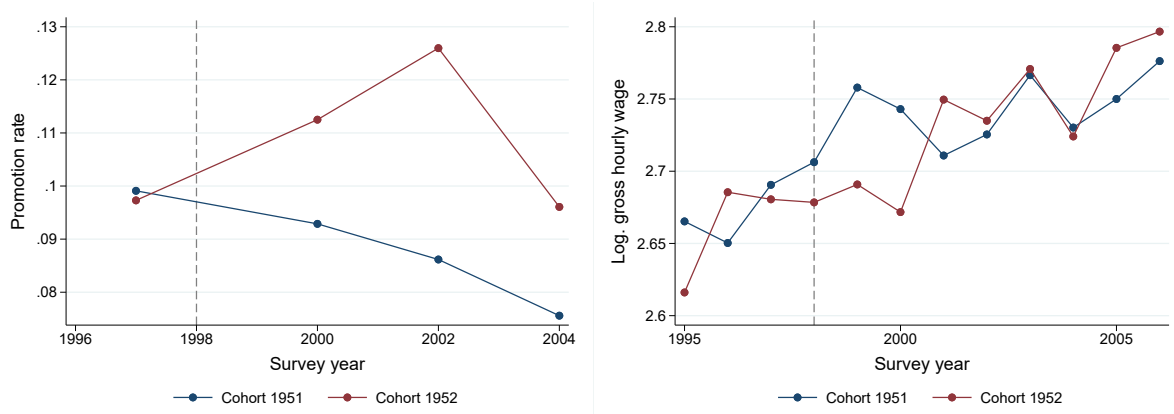
D.2.12 Sensitivity: Estimates on a Common Sample



Notes: The plot shows event study estimates with 95 percent confidence intervals of an increase in the ETR on promotions using ISCO-88 skill levels over time. All coefficients are estimated on a common sample. The vertical red line marks the time of the 2007 reform. Estimates based on employed individuals born between 1953-1964. Data Source: SOEP v36, 2000-2013.

Figure D.12: Promotion Effects on a Common Sample

D.2.13 Sensitivity: The 1999 Pension Reform



(a) Job Promotions

(b) Gross Hourly Wages

Notes: The plots show the the proportion of employed women who were promoted to a higher occupational position relative to the previous observation period based on ISCO skill levels (panel a), as well as the evolution of hourly wage rates (panel b), for cohorts born in 1951 and 1952 before and after the 1999 pension reform (marked by the dashed vertical line). Data Source: SOEP v36, 1995-2006.

Figure D.13: Job Promotions and Hourly Wages before and after the 1999 Pension Reform

Appendix E

Appendix to Chapter 5

For copyright reasons, this chapter is not included in the online version of this dissertation. It is published as Haan, P., Peichl, A., Schrenker, A., Weizsäcker, G., & Winter, J. (2022). Expectation management of policy leaders: Evidence from COVID-19. Journal of Public Economics, 209, 104659.

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Summary

This dissertation consists of five independent chapters contributing to the field of applied economics. The first three chapters analyze workers' perceptions of the wage penalty associated with working part-time, further evaluating the labor supply implications of biased beliefs. Chapter 4 quantifies the effects of raising the normal retirement age on the career trajectories of middle-aged workers far from retirement. Chapter 5 examines the expectation management of the German government in the early phase of the COVID-19 pandemic.

Chapter 1 - Do Women Expect Wage Cuts for Part-Time Work?

The first chapter quantifies the perceived changes in hourly wage rates associated with working different hours on the same job for a representative sample of female workers. While part-time working women expect significant hourly wage gains from switching to full-time work - 7 percent on average - full-time workers expect no effect on current wages when switching to part-time, on average. Perceived pecuniary losses from part-time work are most pronounced among full-time working mothers and women in managerial jobs. Using density forecasts, the analyses reveal a large uncertainty about the perceived pay gap that correlates with the probability to report extreme wage penalties, as well as with worker characteristics. Comparing beliefs with selectivity-corrected estimates of the objective part-time penalty further indicates that full-time workers on average underestimate part-time wage losses, whereas part-time workers tend to overestimate full-time wage gains.

Chapter 2 - Causal Misperceptions of the Part-Time Pay Gap

The second chapter studies if workers infer from correlation about causal effects in the context of the part-time wage penalty. Differences in hourly pay between full-time and part-time workers are strongly driven by worker selection and systematic sorting. Ignoring these selection effects can lead to biased expectations about the consequences of working part-time on wages ('selection neglect bias'). Based on representative survey data from Germany, I document substantial misperceptions of the part-time wage gap. Workers strongly overestimate how much part-time workers in their occupation earn per hour, whereas they are approximately informed of mean full-time wage rates. Consistent with selection neglect, those who perceive large hourly pay differences between full-time and part-time workers also predict large changes in hourly wages when a given worker switches between full-time and part-time employment. Causal analyses using a survey experiment reveal that providing information about the raw part-time pay gap increases expectations about the full-time wage premium by factor 1.7, suggesting that individuals draw causal conclusions from observed correlations. De-biasing respondents by informing

them about the influence of worker characteristics on observed pay gaps mitigates selection neglect. Subjective beliefs about the part-time/full-time wage gap are predictive of planned and actual transitions between full-time and part-time employment, necessitating the prevention of causal misperceptions.

Chapter 3 - Biased Wage Expectations and Female Labor Supply

The third chapter quantifies the effects of biased wage expectations on female labor market outcomes. A wide sample of full-time and part-time employees report counterfactual predictions about their own wage trajectories in future full-time and part-time employment, revealing that beliefs about wage growth in part-time employment are severely upward biased. Actual wage growth occurs almost exclusively in full-time work whereas it is close to zero in part-time work, as we show with reduced form estimations and a structural life-cycle model. Subjective expectations, by both full-time and part-time workers, fail to predict the difference in growth rates. We leverage the structural model to quantify how biased beliefs influence labor supply choices and wage profiles over the life cycle. The bias increases part-time employment strongly, induces flatter long-run wage profiles, and mutes the effectiveness of two policy reforms that we simulate. The largest impacts of the bias appear for college-educated women, consistent with the large difference between expected and realized wages observed for this group.

Chapter 4 - Working Longer: Causal Effects on Career Trajectories of Raising the Statutory Retirement Age

This chapter studies the effects of raising the normal retirement age on career advancement and earnings growth of individuals far from retirement. Our difference-in-differences identification strategy takes advantage of cohort-specific variation in pension eligibility rules caused by the 2007 German pension reform. We find that an increase in the expected work horizon increases upward occupational mobility and job promotion rates, but we detect no shift in wage dynamics. Similar results are found for an earlier German reform restricting early retirement options among women.

Chapter 5 - Expectation Management of Policy Leaders: Evidence from COVID-19

The final chapter studies how the communication of political leaders affects the expectation formation of the public. Specifically, the chapter examines the expectation management of the German government regarding COVID-19-related regulatory measures during the early phase of the pandemic. We elicit beliefs about the duration of these restrictions via a high-frequency survey of individuals, accompanied by an additional survey of firms. To quantify the success of policy communication, we use a regression discontinuity design and study how beliefs about the duration of the regulatory measures changed in response to three nationally televised press conferences by former Chancellor Angela Merkel and the Prime Ministers of the German federal states. We find that the announcements of Angela Merkel and her colleagues significantly prolonged the expected duration of restrictions, with effects being strongest for individuals with higher ex-ante optimism.

Zusammenfassung

Die vorliegende Dissertation besteht aus fünf Kapiteln, die jeweils einen individuellen Beitrag im Bereich der angewandten Wirtschaftswissenschaften leisten. Die ersten drei Kapitel messen im Zusammenhang mit Teilzeitarbeit wahrgenommene Lohneinbußen, sowie die Konsequenzen verzerrter Lohnerwartungen für Arbeitsangebotsentscheidungen. Kapitel 4 quantifiziert die Auswirkungen einer durch Anhebung des Regelrenteneintrittsalters angestoßenen Verlängerung der Lebensarbeitszeit auf Erwerbskarrieren und Lohnwachstum. Kapitel 5 evaluiert das Erwartungsmanagement der deutschen Regierung in der Frühphase der Corona-Pandemie.

Kapitel 1 - Erwarten Frauen Lohnkürzungen für Teilzeitarbeit?

Das erste Kapitel untersucht auf Basis repräsentativer Befragungen, ob Arbeitnehmerinnen Lohnabschläge für Teilzeitarbeit bzw. Lohnzuschläge für Vollzeitarbeit erwarten. Während teilzeitbeschäftigte Frauen bei einem Wechsel zu Vollzeit mit einem erheblichen Anstieg des Stundenlohns rechnen - im Durchschnitt um 7 Prozent -, erwarten Vollzeitbeschäftigte bei einem Wechsel zu Teilzeit im Durchschnitt keine Stundenlohnkürzungen. Die im Zusammenhang mit Teilzeitarbeit wahrgenommenen Lohneinbußen sind bei vollzeitbeschäftigten Müttern und Frauen in Führungspositionen am stärksten ausgeprägt. Die empirischen Analysen weisen zudem auf eine große Unsicherheit bezüglich des wahrgenommenen Lohngefälles hin. Ein Vergleich mit um Selektionseffekte bereinigten Schätzungen der Teilzeitlohnlücke legt nahe, dass Vollzeitbeschäftigte die mit Teilzeitarbeit einhergehenden Lohneinbußen tendenziell unterschätzen, während Teilzeitbeschäftigte die Lohngewinne durch Vollzeitarbeit überschätzen.

Kapitel 2 - Kausale Fehlwahrnehmungen der Teilzeit-Lohnlücke

Im zweiten Kapitel wird untersucht, ob Arbeitnehmer im Zusammenhang mit der Teilzeitlohnlücke von Korrelation auf Kausalität schließen. Unterschiede im durchschnittlichen Stundenlohn zwischen Vollzeit- und Teilzeitbeschäftigten lassen sich zu einem großen Teil durch messbare Unterschiede in der Zusammensetzung von Vollzeit- und Teilzeitbeschäftigten, beispielsweise hinsichtlich ihrer Berufserfahrung und Qualifikation, erklären. Sind sich Beschäftigte dieser Selektionseffekte nicht bewusst, kann dies zu verzerrten Erwartungen über die Auswirkungen von Teilzeitarbeit auf Löhne führen ('Verzerrung durch Selektionsvernachlässigung'). Auf Grundlage repräsentativer Umfragedaten aus Deutschland dokumentiere ich erhebliche Fehlwahrnehmungen der Teilzeit-Lohnlücke. Während Beschäftigte das durchschnittliche Lohnniveau in Vollzeit in ihrem Beruf nahezu korrekt einschätzen, werden die mittleren Stundenlöhne von Teilzeitbeschäftigten stark überschätzt. Zudem zeigt sich ein Zusammenhang zwischen der geschätzten durchschnittlichen Lohndifferenz von Vollzeit- und Teilzeitbeschäftigten und den geschätzten Lohn-

veränderungen bei einem hypothetischen Wechsel zwischen Vollzeit und Teilzeit. Ergebnisse eines Umfrageexperiments legen nahe, dass Beschäftigte kausale Schlussfolgerungen aus der reinen Korrelation zwischen Teilzeitarbeit und Stundenlöhnen ziehen. So erhöht sich die erwartete Vollzeitlohnprämie um den Faktor 1,7, wenn Individuen Informationen über die durchschnittliche Lohndifferenz zwischen Vollzeit- und Teilzeitbeschäftigten vorliegen. Erhalten die Befragten zusätzliche Informationen darüber, dass beobachtbare Lohndifferenzen durch Unterschiede in der Qualifikation erklärt werden können, reduziert sich der Zusammenhang deutlich. Da subjektiv wahrgenommene Lohngefälle zwischen Vollzeit und Teilzeit mit geplanten und tatsächlichen Arbeitsangebotsentscheidungen korrelieren, ist es wichtig, kausale Fehlwahrnehmungen zu erkennen und zu vermeiden.

Kapitel 3 - Verzerrte Lohnerwartungen und das Arbeitsangebot von Frauen

Das dritte Kapitel untersucht die Erwartungen von Frauen hinsichtlich der langfristigen Entwicklung von Vollzeit- und Teilzeitlöhnen und quantifiziert die Auswirkungen verzerrter Lohnerwartungen auf Arbeitsangebotsentscheidungen. Anhand kontrafaktischer Vorhersagen über den erwarteten Lohnverlauf bei zukünftiger Vollzeit- und Teilzeitbeschäftigung zeigt sich, dass Frauen das Lohnwachstum in Teilzeitbeschäftigung signifikant überschätzen. So finden Lohnzuwächse fast ausschließlich in Vollzeitarbeit statt, während in Teilzeit nur geringfügige Lohnzuwachsraten realisiert werden. Dahingegen können subjektive Erwartungen den Unterschied in den Lohnwachstumsraten nicht vorhersagen. Anhand eines strukturellen Lebenszyklusmodells können wir den Einfluss verzerrter Lohnerwartungen auf Arbeitsangebotsentscheidungen und Lohnpfade im Lebensverlauf quantifizieren. So führen die Wahrnehmungsverzerrungen zu einer Erhöhung von Teilzeitbeschäftigung sowie zu flacheren Lohnprofilen; zudem wird die Wirksamkeit zweier von uns simulierter Politikreformen gedämpft. Die Fehlwahrnehmungen sind bei Frauen mit Hochschulbildung am stärksten ausgeprägt, entsprechend sind die Auswirkungen auf Arbeitsangebot und Löhne für diese Gruppe am größten.

Kapitel 4 - Länger arbeiten: Kausale Auswirkungen einer Anhebung des Renteneintrittsalter auf Erwerbskarrieren

Dieses Kapitel untersucht die Auswirkungen einer durch Anhebung des Regelrenteneintrittsalters angestoßenen Verlängerung des Erwerbslebens auf Berufsaufstieg und Lohnwachstum. Das Regelrenteneintrittsalter in Deutschland wurde 2007 für alle nach 1946 geborenen Geburtsjahrgänge schrittweise von 65 auf 67 Jahre erhöht. Unsere Identifikationsstrategie basiert auf einem Differenzen-in-Differenzen Ansatz, welcher sich die quasi-exogene kohortenspezifische Variation im erwarteten Renteneintrittsalter zu Nutze macht. Die empirischen Analysen zeigen, dass eine Verlängerung der erwarteten Erwerbsdauer die berufliche Mobilität erhöht. Gleichzeitig stellen wir jedoch trotz einer Erhöhung der Berufsaufstiegsraten keine Veränderungen in der Lohndynamik fest. Unsere Ergebnisse bestätigen sich auch für eine frühere Reform des deutschen Rentensystems, welche die Frühverrentungsoptionen für Frauen ab Jahrgang 1952 eingeschränkt und somit die erwartete Lebensarbeitszeit verlängert hat.

Kapitel 5 - Das Erwartungsmanagement politischer Entscheidungsträger: Evidenz aus der Corona-Pandemie

Im letzten Kapitel wird untersucht, wie sich die Kommunikation politischer Entscheidungsträger auf die Erwartungsbildung der Öffentlichkeit auswirkt. Konkret evaluieren wir das Erwartungsmanagement der deutschen Regierung in der Frühphase der Coronapandemie und untersuchen die Reaktionen auf die Ankündigung coronabedingter Regulierungsmaßnahmen. Hierzu ermitteln wir die subjektiv wahrgenommenen Erwartungen hinsichtlich der Dauer verschiedener Alltagsbeschränkungen anhand einer Hochfrequenz-Befragung in der Bevölkerung und einer zusätzlichen Befragung von Unternehmen. Wir betrachten drei bundesweit übertragene Pressekonferenzen der ehemaligen Bundeskanzlerin Angela Merkel und der Ministerpräsidenten der deutschen Bundesländer und untersuchen, wie sich die Erwartungen hinsichtlich der Dauer der Beschränkungen als Reaktion auf die Pressekonferenzen veränderten. Um den Erfolg der politischen Kommunikation empirisch zu quantifizieren, nutzen wir ein Regression Discontinuity Design (RDD). Unsere Untersuchungen zeigen, dass die Ankündigungen der politischen Entscheidungsträger die erwartete Dauer der Beschränkungen signifikant verlängerten. Dabei waren die Effekte am größten bei Personen mit einem starken ex-ante Optimismus.

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