Promotion prospects and within-level wage growth: A decomposition of the part-time penalty for women *

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Abstract

I study the life-cycle pattern of part-time employment and its impact on wage growth in female careers. I show that the part-time wage penalty consists of two essential components: i) a penalty for promotions and ii) a within-career-level wage penalty. Using dynamic structural modeling, I quantify the relative importance of the channels. The penalty for working half a day for two consecutive years in one's early thirties is one Euro per hour. 70% of it is due to slowdowns in experience accumulation within career levels. A part-time spell of four years marks the point at which forgone chances of promotion and within-level wage losses contribute to the wage penalty to an equal degree. Counterfactual simulations demonstrate that financial incentives to increase the time spent working can be well complemented by policies which ensure that experienced young women are promoted early in their careers.

Keywords: Wage Growth, Female Labor Supply, Part-Time, Promotions

JEL classification: J21, J22, J24, J31

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1. Introduction

In the developed economies of the 21st century, women are participating in the labor market in increasing numbers (OECD 2022). However, gender-based wage gaps persist. One important reason for this is women's high rate of part-time employment (Petrongolo 2004, Goldin 2014, Cortés & Pan 2019). For many female employees, wage stagnation is a dynamic consequence of part-time work. Hourly wage penalties arise because part-time spells are associated with slowdowns in experience accumulation (Blundell et al. 2016, Costa Dias et al. 2020). Thus far, the exact mechanisms by which experience penalties hamper wage growth have not been studied in detail.

In this paper, I argue that foregone human capital accumulation in part-time employment can reduce the likelihood of promotions to higher career levels and that part-time work also hinders wage growth conditional on employees' career levels. Determining the reasons why part-time employment leads to lower wage is valuable. Knowledge about the relative importance of the factors I study, and the timing of their occurrence, can help policymakers intervene effectively to close the part-time wage gap.

Using a dataset representative of women with tertiary education in Germany, I break down the long-run part-time wage gap into two distinct components and quantify the size of their relative effects. I differentiate between i) a penalty for promotions and ii) a within-career-level wage penalty. My analysis employs a dynamic labor supply model featuring hierarchical wage structures and promotions. It captures long-run effects of the part-time penalty in experience and allows me to perform a series of counterfactual policy simulations. Bringing the model to the data, I demonstrate that part-time employment leads to wage stagnation through both channels. The typical employment pattern for the majority of women in the sample - to work half a day instead of full time for two consecutive years in their early thirties following the birth of a child - results in a wage penalty of ca. one Euro per hour. More than two-thirds of this is due to the penalty in experience accumulation which translates into lower hourly wages regardless of the career level of employment. These within-level wage penalties are three times more severe at high as compared with low career-level jobs. This notable difference in the size of the penalty between the two career levels is explained by the fact that returns to experience are substantially higher in high career-level jobs. The remaining third of the hourly wage losses is due to forgone chances to receive a promotion and to permanently switch to a higher wage trajectory. The relative contribution of the effects reverses if individuals reduce their working hours for multiple years or if worktime reduction is more drastic, e.g., if women work only eight hours per week. Counterfactual analysis based on the estimated structural model shows that two policies commonly discussed in the public debate on gender gaps - childcare cost reductions and tax reforms - do increase labor market attachment and earnings, but do not leverage the fact that wages increase as women progress in their careers. Therefore, a policy mix which ensures higher promotion rates for qualified females and provides financial incentives to increase hours of work regardless of the career status is necessary to help close the part-time wage gap, and improve gender balance at the upper levels of the career ladder at the same time.

The partial equilibrium model of working hour choices I develop to discern and quantify the mechanisms that cause the part-time penalty is based on the life-cycle framework as featured in Keane & Wolpin (2010), Blundell et al. (2016), and Adda et al. (2017). My modeling approach explicitly incorporates career hierarchies and promotions in the dynamic optimization problem. The key feature in the model is that the probability of promotion and the speed of within-level wage growth both depend on accumulated human capital. In turn, experience accumulation is a function of the history of working hour choices, where penalties apply: working less than full time is worth less than a full-time experience equivalent. The model design, thus, stipulates that the experience accumulation penalty within levels and the promotion prospect penalty between levels are two distinct contributors to wage stagnation. Moreover, the model enables the quantification of each penalty separately, such that the relative size of the two factors can be evaluated. The assumptions in the model address selection explicitly, such that results obtained from estimating the model have a causal interpretation. Observed drivers of selection - interactions between child arrival, child-rearing, and the propensity to work part time - are captured via a series of preference parameters associated with the presence of children in different age groups. Selection due to unobserved factors is accounted for through unobserved preference types. Another ingredient that makes the model design particularly suitable for analyzing the components of the part-time penalty concerns its choice set. Choices on the intensive margin are continuous, and modeling is such that a small and a large reduction of working hours each affects both the probability of promotion and the speed of within-level experience accumulation, but to different degrees. This feature is essential because reduced form evidence from earlier studies suggests that part-time penalties are highly non-linear in the number of hours worked. Estimates of the part-time penalty in experience accumulation are obtained via a simulated moments (MSM) procedure and subsequently used to analyze the dynamic effects of policies aimed at mitigating the part-time penalty.

The empirical analysis in the paper draws on data from the German Socio Economic Panel Study (SOEP). The latest waves of the survey contain key information about individual job levels from a revised occupation classification, KldB 2010, allowing me to differentiate between two career levels. Low-level occupations have comparatively low skill and knowledge requirements and pay low wages. High-level occupations carry more responsibilities, require specific professional knowledge, and offer higher wage rewards. The SOEP contains data on monthly earnings, working hours, and past work experience, which is crucial to my work for two reasons. First, wage growth and part-time penalties can be analyzed based on hourly wages. Second, human capital accumulation can be measured as a function of the precise number of hours worked. The data set also features detailed information on children, which allows for explicit modeling of the effects of child arrival, putting the part-time penalty into the context of motherhood.

Descriptive analysis of the data yields several key insights that motivate the design of the life-cycle model used for empirical analysis. First, high-level occupations exhibit a notably higher wage trajectory than low-level occupations. Second, decomposing the variance in repeated individual wage observations suggests that career levels play a significant role in explaining the wage level. Finally, there is evidence that the probability of promotion depends positively on the number of hours worked. Consequently, modeling simultaneously a) wage increases upon promotion and b) within-level wage growth is critical for understanding how part-time work hinders wage growth.

Bringing the model to the data yields two sets of findings. First, the model estimation quantifies the relative size of within-level experience accumulation penalty and the penalty for individual career progression. Second, the counterfactual policy analysis I perform tests the effectiveness of childcare cost and income tax reductions in mitigating wage stagnation brought about by part-time work.

The first set of results suggests that the high career level is associated with a higher baseline wage and steeper returns to experience. In comparison, experience hardly generates wage growth at the low career level. Part-time spells trigger both within-level wage penalties and promotion penalties. According to the estimation, a year of working 20 hours per week is worth 0.41 full-time equivalent years. A median individual experiences a penalty of one Euro per hour following two years of part-time work at ages 31 and 32. Due to the difference in speed of human capital accumulation at the two career levels, the within-level penalty at the high level is approximately three times that at the low level. The yearly gross part-time penalty in earnings after four years of part-time employment amounts to 2,370 Euros. It is precisely the spell length of four years that marks the point at which forgone chances of promotion and within-level wage losses contribute to the wage penalty to an equal degree. For more extended periods of part-time work, foregone promotion opportunities contribute to a greater degree to the overall part-time penalty than do within-grade wage losses. Missing the jump to the wage trajectory of a high career level job becomes the dominant force when part-time employment persists.

Based on the above findings, I analyze how policymakers can act to close the part-time gap, and by extension, the gender wage gap. To this end, I consider two hypothetical policy changes and study their effects in a set of counterfactual simulations. The first policy I analyze is a decrease in childcare costs by 10%. In the new regime, working hours increase by 1.75 hours of work per week, or 5.8%, on average. The expansion in worktime translates into a 6% increase in lifetime earnings from employment. However, the increase in hourly wages is markedly lower. In the mean, these increase by 9 Euro cents per hour, corresponding to 0.41% of the average wage. The increase in lifetime earnings is, thus, driven mainly by the mechanical effects of the increase in working hours rather than by a mitigation of the part-time penalty, which is reduced only to a small degree. The generated increase in working hours is not sufficient to increase promotions significantly, nor to compensate for much of the within-career-level penalty.

The second policy I evaluate is a proportional reduction in the income tax rate. While childcare cost reductions affect mothers only, this policy presents a change in the incentive structure for all agents in the model. It induces an increase in the hours of work per week of 2.7 on average. Correspondingly, lifetime earnings from employment increase by 10%. As in the scenario with lower costs of childcare, this scenario does not yield a sizable increase of employment at high career level. In both cases no additional promotions for individual aged 26-32 take place, because already in the baseline scenario the number of workers eligible for a promotion exceeds the number of workers who can be promoted. Therefore, a policy mix that increases hours worked, but also ensures that more qualified females are promoted to high career level jobs is necessary to close the part-time wage gap and contribute to increasing equality in pay and in the female representation at the top of the career ladder.

The remainder of this paper is organized as follows. The next section links the paper to previous research. Section 3 describes the data used to derive empirical conclusions. Section 5 presents the life-cyle model in detail. Section 6 explains the estimation methods used. Sections 7 and 8 describe estimation results, the key findings of the part-time penalty decomposition, and insights for policy design from counterfactual simulations. Section 9 concludes.

2. Literature

A vast economic literature, heatedly debated among scholars and policymakers, considers the reasons for different types of gender pay gaps. The various strands of the literature explore distinct gaps, some of which co-occur. Broadly, this paper examines the female labor supply and how it relates the topics of the part-time penalty, the motherhood penalty, and the penalty in occupational attainment at the top levels of a career ladder. Since all of these topics contribute to explaining the gender pay gap, the paper also speaks to the considerable literature on wage gaps in general.

In Germany, part-time employment is a widespread phenomenon (OECD 2022). Therefore, various part-time penalties are likely principal factors in the gender pay gap. Yet conclusions about the relationship between part-time work and wage growth vary. For example, Manning & Petrongolo (2008) argue that the substantial part-time penalty they observe in British data almost wholly disappears after controlling for observable characteristics, and most importantly, occupations. At the same time, research using data from Germany generally documents significant penalties for very low working hours and lower or no penalties for modestly reduced hours. Wolf (2002) finds a robust non-linear relationship between work hours and wages, with a penalty for working 20 hours or fewer and a premium for overtime. Similarly, Paul (2016) emphasizes that part-time work of 15 hours or fewer is more strongly associated with a penalty than other sorts of part-time work. In light of this evidence, a rigorous causal analysis of part-time penalties must control for key observable characteristics and consider different degrees of reduction in working hours. The estimation in this paper takes education, the presence and age of children, and career levels of individuals into consideration. It relies on a continuum of working hours between 0 and 48 as possible labor supply choices.

In a more recent study for Great Britain, Costa Dias et al. (2020) find that full-time work has a strong positive impact on wage growth, which increases with education, while part-time work has little or no positive effects on wage evolution. A related finding is reported in Blundell et al. (2016), where the authors posit a fully-fledged life-cycle labor supply model. Parameter estimates suggest that depending on the level of education, an additional year of part-time work adds no more than one-fifth of a full-time-equivalent year to one's human capital stock. Thus, part-time employment barely counteracts depreciation and does not generate significant wage growth. Using different econometric techniques, both Blundell et al. (2016) and Costa Dias et al. (2020) take the dynamic effects of part-time employment on human capital accumulation into account. Contrasting their results with findings of no static effects of part-time work on wages, see, e.g., Schrenker (2023) allows one to conclude that the wage penalty associated with part-time employment is dynamic. The modeling approach in the paper at hand is similar to the framework in Blundell et al. (2016), in that it analyzes dynamic life-cycle effects explicitly. My findings support the claim that the one-period-ahead penalty is rather small, but the penalty for working part time for extended periods is substantial. In particular, I argue that to a large extent, the wedge between part-time and full-time wages opens up because promotion opportunities are foregone when one is working part time.

Part-time spells and career interruptions for females are strongly correlated with the presence of young children in the household. Looking at childbirth in an event study framework, Kleven et al. (2019) show that motherhood gives rise to "a long-run gender gap in earnings," caused by, among other things, a reduction in hours worked. The Danish data in the study show that mothers have a lower probability of becoming managers while being more likely to choose public sector jobs. In an experimental study, Correll et al. (2007) find that employers perceive mothers to be less competent and less committed than other workers. As a result, they are judged by higher standards regarding expected test scores and receive lower recommended salaries than non-mothers. In the study, the proportion of mothers recommended for hire, promotion, and management positions is lower than the proportion of non-mothers. In their dynamic life-cycle analysis of the motherhood penalty in Germany, Adda et al. (2017) find that career penalties even precede the arrival of children, as forward-looking agents sort along disadvantageous trajectories in anticipation of fertility. In sum, previous literature provides evidence that the presence of children is simultaneously associated with employment interruptions, part-time employment episodes, lower probability of being promoted, and the opening of a persistent earnings gap, all of which affect women in particular. In this paper, I consider the effect of children – in specific those below six years of age - on individual choices on the intensive margin of the labor supply. Employment interruptions and part-time spells following a child's birth are modeled so that they can be structurally related to both wage growth within each level on a career ladder and the probability of being promoted to a higher career level. Thus, the motherhood penalty can be broken down into a pure wage penalty and a career progression penalty.

Several recent studies link the consequences of extended periods of leave and part-time employment to promotion prospects. Based on 1994-2002 data from Belgium, Deschacht (2017) documents that the yearly promotion probability for women is less than half that for men, with statistics being even more skewed for promotions to managerial positions. The paper shows that higher contract hours and a higher propensity for overtime and late work are associated with higher promotion rates. In the internal labor market of a Chinese firm, Zhang (2019) finds a gender gap in promotion probability, years to promotion, and wage increases upon promotion. In this data, selection into occupations explains much of the gap in promotion premiums, almost two-thirds of the gap in promotion speed, and half the gap in probability of promotion. The remaining probability gap is associated with human capital. Hospido et al. (2022) look at one institution alone - the European Central Bank - and employ data that allow them to differentiate between applications for promotion and promotions upon application. The results suggest that conditional on applying for a promotion, there is no gender difference in receiving a promotion. However, women are less likely to apply, which correlates with part-time work and children. The data I use for empirical analysis does not allow for differentiation between the propensity to apply for a promotion and the probability of being promoted conditional on applying. Promotions are observed as an equilibrium outcome of the application process[1]. This aggregation is a disadvantage that is hard to overcome in a country-wide analysis, since data on job applications are generally unavailable on such a large scale. The data I employ have the advantage of representing a random sample of the entire German population. Consequently, results from the estimation I perform are well suited to policy analysis, as they do not reflect the status quo of one firm or industry alone but offer a representative economy-wide view of the female workforce.

A second key finding in Hospido et al. (2022) is that promotions are essential for wage growth. The authors find that a large portion of the wage gap occurs between levels and conclude: "[...] promotions are a major contributor to the gender wage gap." (p.988). In another paper, Bayer & Kuhn (2018) decompose life-cycle wage growth into several components and state that "it is promotions along the hierarchy dimension that are key to explaining average wage growth", (p.14)[2]. These findings motivate the inclusion of two distinct career levels in the model I develop in Section 5.

The exact mechanism explaining how wages increase with promotions is motivated by the micro-theoretical literature. The seminal paper in this field, Lazear & Rosen (1990), proposes a tournament model and argues that empirical facts can be rationalized based on women's lower probability of being promoted. Booth et al. (2003) offer a model of sticky floors, explaining differential increases

[1]Notably, the population I analyze consists of women who all hold education qualifications sufficient for eligibility for promotion. As Appendix V suggests, a significant fraction of the individuals surveyed in 2018 expects a promotion within the firm of current employment in the 2 following years. As the of promotions I employ include upward career moves within and between employers, I expect that an even higher share of the population is interested in a promotion.

[2]The comment refers to the sample of male employees the authors study. They note that the lack of wage growth over the life cycle they observe for women is due to the slower progression of women up the career ladder, (p. 15).

in pay upon promotion in terms of heterogeneity in outside opportunities and productivity. The framework is extended to multiple hierarchy levels in Zucco & Bächmann (2020). In turn, Gicheva (2013) proposes a two-period career ladder model where labor supply choices depend on the heterogeneous preferences of workers, while wage functions at distinct career levels reward human capital differently. I transfer the notions of career levels and promotion from Gicheva (2013) to the dynamic discrete choice framework of Keane & Wolpin (1997, 2010), Blundell et al. (2016) and Adda et al. (2017). The model I propose enables me to decompose the life-cycle part-time wage gap into a gap in the likelihood of receiving promotions and a gap in wages conditional on career level. The model can disentangle the two components of wage stagnation and capture their dynamic effects while controlling for selection on both observable and unobservable characteristics. The results obtained using the model have causal authority and can thus guide policy targeted at closing the part-time wage gap, and by extension, the gender wage gap. In this way, the paper contributes to the broad literature on gender pay gaps (Goldin 2006, 2014, Blau & Kahn 2017, Granados et al. 2020). I find that promotions are highly relevant for wage growth, as they propel individuals to significantly higher persistent wage trajectories. Consequently, policies that increase full-time employment early in the life cycle, and thus induce more promotions, effectively reduce wage gaps.

3. Data

3.1 Data source

The empirical analysis in this paper is drawn from the German Socio Economic Panel Survey (SOEP). The data set has two distinct advantages, making the SOEP suitable for studying the interactions between working hour choices, wage growth, and promotion. First, the data include detailed information on individual biographies, labor market situations, and family composition. Among other key pieces of information, the data provide measures of contractual and overtime working hours. The analysis at hand can thus target hourly wages and track wage growth and promotions as functions of the choice of how long to work[3]. Second, SOEP data feature a classification of the occupations of all individuals interviewed. Notably, in 2010, the classification scheme (KldB) was revised and extended to facilitate not just horizontal but also vertical differentiation among occupations. Since 2013, yearly panel survey records include indicators for the level of expertise and associated level of responsibility of each occupational position. The availability of such indicators allows me to infer the career level of each individual studied and motivates the construction of the estimation sample, described next.

[3] In contrast, administrative labor market data in Germany do not include a measure of working hours, but rather track daily earnings instead, see Antoni et al. (2019). The lack of working hours and hourly wage measures renders the analysis of the effect of working hour choices on human capital accumulation impossible.

3.2 Estimation sample

The estimation sample is an unbalanced panel of females present in the SOEP between 2013 and 2020, the inaugural year being the point at which a variable indicating seniority was introduced and the ending year the latest currently available for scientific use. The sample is confined to individuals with tertiary education. Specifically, it includes women who have obtained a vocational degree, a university degree, or a graduate or professional degree. I choose to focus on these high-educated women because they have the best career prospects, on the one hand, and their wage growth suffers most as a result of part-time spells, on the other, see e.g., Blundell et al. (2016), Costa Dias et al. (2020)[4].

The sample includes all women who are part of the labor force aged 26 to 55. In Germany, for the cohort represented in the data, the average age of entry into the labor market ranges from 26.5 years in 2013 to 23.5 years in 2020[5]. The last years of employment before retirement appear irrelevant as far as chances to be promoted to a high career level are concerned, as promotions of individuals above the age of 55 are very rare in the data[6]. Therefore, I avoid modeling individuals approaching retirement and focus on the earlier stages of the life cycle. I find that working hour choices in childbearing years are strongly associated with the part-time penalty in experience accumulation. Ultimately, this penalty increases within-level wage stagnation and reduces the rate of promotion. I note that my sample excludes civil servants, self-employed persons, pensioners, those receiving education or training, and those performing military or community service. I also exclude disabled individuals and apprentices.

The final sample considers 3,443 females and consists of 12,342 person-year observations. Table 1 presents summary statistics of the key variables in the data set.

The average age in the sample is 39.17 years. Fifty-six percent of the individuals studied have had a child at some point. In the mean, there are 0.71 children per household. The median age at first birth is 30. The SOEP data contain several measures of earnings from employment and hours worked that can be used to calculate each individual's hourly wage. The analysis is performed using an individual's gross monthly income from employment and her agreed-upon working hours. Wages are translated to 2020 equivalents. The average gross hourly wage in the sample is 23.07 Euros. In the mean, working contracts specify 33.61 hours of work per week. In addition to agreed-upon working hours, employed individuals report an average of 2.11 hours of overtime. 51% of the

[4]Appendix I presents mean sample characteristics for the period 2013-2019 and the year 2020. The lack of significant differences suggests that the high-educated women included in the sample were not, or at least not yet, affected by the labor market turmoil which resulted from the COVID-19 pandemic.

[5]*Statistisches Bundesamt. (3. September, 2021). Durchschnittsalter von Hochschulabsolventen* in Deutschland in den Prüfungsjahren von 2003 bis 2020 (in Jahren) [Graph].In Statista* (n.d.), accessed 2022-05-25.

[6]In addition, health shocks and informal care for one's spouse or parents become increasingly important for time allocation choices among older workers. Accounting for such circumstances would significantly increase the requirements on the data without adding much value to the analysis of career development.

Table 1: Descriptive Statistics

	Mean/Share	Median	S.D.	Min	Max
Age	39.17	38.00	8.53	25.00	55.00
Motherhood	0.56	1.00	0.50	0.00	1.00
Number of Children in Household	0.71	0.00	0.94	0.00	7.00
Age at first Child	29.79	30.00	5.03	16.00	44.00
Contractual Working Hours	33.55	38.00	8.39	2.00	70.00
Overtime Hours	2.11	1.00	2.97	0.00	23.00
Gross Hourly Wage	23.07	21.70	8.80	8.36	59.21
Employment Status					
Non-Working (%)	0.18				
Part-Time (%)	0.31				
Full-Time (%)	0.51				
Promotion	0.11				
Individuals	3443				

Notes: Estimation sample. SOEP 2013-2020. Unbalanced panel of women with high education (N=12,342). Ages 26 to 55. Motherhood indicates the fraction of women who become mothers at some point in their lives. Hourly wages are calculated based on contractual working hours and gross monthly earnings. Adjusted to 2020 Euro equivalents. Employment status as per categorical self-reported classification. Promotion indicates the fraction of individuals observed at a minimum of two points in time who have experienced a promotion.

person-year observations correspond to years of full-time work and 31% to part-time employment. In the remaining 18% of observations, individuals state that they do not work. Eleven percent of individuals that have responded to at least two waves of the SOEP survey are observed to have been promoted from low to high career level jobs during the analysis period.

The definition of promotions and the measurement of occupation levels in the data are discussed in detail in the following subsection.

3.3 Occupation levels

For each person-year observation in the estimation sample, a level on the career ladder - low or high - is assigned based on the Classification of Occupations 2010 (KldB, 2010)[7]. In 2010, the German Federal Employment Agency revised its formal classification of occupations in the interest of modernization and improving comparability to the International Standard Classification of Occupations 2008, ISCO-2008. Jobs of SOEP respondents are classified according to the KldB 2010 from 2013 onward.

The job of each interviewee in the analyzed SOEP sample is assigned a five-digit code from the KldB 2010[8]. The first four digits facilitate horizontal differentiation of 700 distinct occupations. The fifth digit distinguishes between up to four horizontal levels within each occupation. The

[7]For more information on the methods and codes of the classification, see *Klassifikation der Berufe 2010 – berarbeitete Fassung 2020 Band 1: Systematischer und alphabetischer Teil mit Erläuterungen* (2021).

[8]The survey item used for the classification is presented in Appendix II

horizontal levels represent groups of jobs with increasing skill and knowledge requirements within the same occupation. The lowest level corresponds to simple, routine-task jobs with low complexity that require low or no specific knowledge. Level 2 corresponds to relatively more complex jobs that require some specific knowledge of the profession. Levels 3 and 4 indicate jobs of higher and highest complexity and specific knowledge requirements.

To give a clear idea of the types of occupations and jobs the classification distinguishes, Table 2 lists the occupations and examples of associated jobs that are most frequently observed at each of the four levels. *Level 1* typical careers include jobs in cleaning, storage, geriatric care, cooking, and guest services such as *geriatric care nurse, kitchen assistant, or waitress.* Examples of common *Level 2* jobs in the data include *information desk assistant, cashier in a bank, and nurse.* Jobs at career *Level 3* and *Level 4* are predominantly those typical of larger organizations, such as *assistant accountant, management assistant, social media manager*, jobs in education and research (*teachers and professors*), and highly skilled jobs such as *medical doctors.*

For the purposes of empirical analysis, I map *Levels 1 and 2* to the low career level and Levels 3 and 4 to the high career level. I choose to aggregate the four levels into two broad categories for the following reasons. Empirically, *Levels 3 and 4* are very similar in terms of wage profiles, and by extension, the implied wage function, see Appendix III. They differ substantially from the lower two levels. While *Levels 1 and 2* also seem to differ from one another in terms of the wage function, less than 3% of person-year observations accrue to *Level 1.* Therefore, I do not look at three levels but rather at career groups, low and high.

A promotion is observed whenever an individual previously employed in a low-career-level job switches to a job at the high career level. A promotion is always associated with a switch in tasks one performs on the job. Promotion implies that task complexity increases. Therefore, promotion must not entail switching occupations. Promotion can be associated with but is not limited to a match with a new employer. Importantly, all women in the sample are sufficiently qualified in terms of the education they have received to perform a job at the high career level.

4. Descriptive evidence

This subsection provides descriptive evidence supporting the hypothesis that the choice of reduced working hours has negative consequences for wage growth in the absence of promotion, and also for triggering promotion. First, I discuss the differences between wages and working hours at both career levels. Second, I present a decomposition of the variance in the repeated wage observations that implies that career levels are strong predictors of the individual wage level. Third, I provide descriptive evidence that moving upward from a low to a high career level job correlates positively with working long hours. Each point of the reduced form argument clarifies why the causal life-cycle analysis necessitates a structural model, and thus represents motivation for the model design.

Table 2: Examples of frequently observed jobs in each occupation level

	Occup. Nr.	Occup. Title	Job Example
Level 1			
	54101	Jobs in Cleaning	Cleaning Assistant
	51311	Jobs in Warehousing	Bottler
	82101	Jobs in Geriatric Care	Geriatric Care Assistant
	29301	Kitchen Staff	Kitchen Assistant
	63301	Jobs in Gastronomy	Service
Level 2			
	83112	Jobs in Childcare and Education	Caretaker
	71402	Office Management	Counter Information Assistant
	71302	Jobs in Commerce and Technical Consulting	Assistant in Commerce
	72112	Bank Clerk	Cashier (Bank)
	81302	Jobs in Medicine and Nursing	Nurse
Level 3			
	72213	Jobs in Accounting	Assistant / Professional Accountant
	92113	Jobs in Advertising and Marketing	Social-Media-Manager
	71393	Executive Business Organisation	Agile Coach / Scrum Master
	71403	Office Management	Management Assistant
	73283	Jobs in Administration	Professional Administration
Level 4			
	83124	Jobs in Childcare and Education	Career Advisor
	84124	Teachers in Secondary Schools	Teacher
	81404	Medical Doctors	Pediatrician
	84304	Jobs in Higher Education and Research	University Professor
	84114	Teachers in Primary School	Teacher

Notes: Examples of occupations and jobs in each respective occupation from KldB 2010, *VII Systematisches Verzeichnis der Berufsbenennung, pp. 126 - 212.* Examples were chosen as the five most frequent occupations for each occupation level present in the estimation sample of the SOEP as described in the main text. The leftmost column contains the occupation code, the last digit in the code stands for the occupation level (1-4). The middle column contains the name of the occupation category. The rightmost column contains one example of a job in the category. Text columns translated from the document's original language, German, into English by the author.

4.1 Descriptive analysis by career level

Table 3 summarizes principal differences in characteristics between individuals employed at the low and high career levels. For example, the mean gross hourly wage at the low level is 17.90 Euros, while the mean hourly wage at the high career level amounts to 24.90 Euros. Similarly, the agreed-upon and the overtime working hours are reported higher at the high career level, by 2.26 and 0.72 hours per week, respectively. All differences are statistically significant at all conventional significance levels.

Table 3: Descriptive Statistics by Career Level

	Career Leevel Low				Career Level High			
	Mean/Share	S.D.	Min	Max	Mean/Share	S.D.	Min	Max
Age	42.05	8.75	25.00	55.00	38.76	8.56	25.00	55.00
Number of Children in Household	0.61	0.87	0.00	5.00	0.57	0.87	0.00	5.00
Contractual Working Hours	31.95	8.93	2.00	60.00	34.21	8.02	3.00	70.00
Overtime Hours	1.60	2.56	0.00	23.00	2.32	3.08	0.00	23.00
Gross Hourly Wage	17.90	6.70	8.36	59.11	24.90	8.74	8.46	59.21
Observations	2620				6057			

Notes: Estimation sample. SOEP 2013-2020. Unbalanced panel of women with high education (N=3,443). Ages 26 to 55. Years of employment in a job classified as *Level 1* or *Level 2* are aggregated to 'Career Level Low' observations. Years of employment in a job classified as *Level 3* or *Level 4* are aggregated to 'Career Level High' observations. 3,665 person-year-observation consist of periods individuals spent out of work, a status not assigned a career level.

Figure 1 shows wage and working hour profiles by age for each career level. Wages at the low career level are visibly lower. Low-career-level individuals reach the highest average wage in their late forties. The peak wage for those in low-level careers is approximately the same as the starting average wage that individuals at the high level earn in their late twenties. The wage increases that workers at the high level receive are much steeper than the increases received by workers at the low level. Peak average wages at the high level are reached at around 40. The wage profile flattens out for the remaining 15 years of the analysis period. Reported working hours at the high level are longer over the entire life cycle. While hours at the low level stay at around 35 per week for ages 30-55, working hours for those at the high level drop in the middle of the life cycle and increase back to 40 hours per week at the end of the observation period.

The illustration in Panel (a) suggests that even after conditioning for high education, the range of gross hourly wages is broad. Career level appears to be a significant predictor of wage level. Further, a detailed look at wage evolution for jobs at both low and high levels suggests that returns to experience also differ by career level. Panel (b) indicates that working hours are shorter at the low-career level. It is unclear whether low rewards induce short hours, or whether wage penalties for reduced hours of work lead to a flat wage profile. Finally, it should be noted that low wages, stagnant wage

(a) **Gross Hourly Wages** (b) **Working Hours**

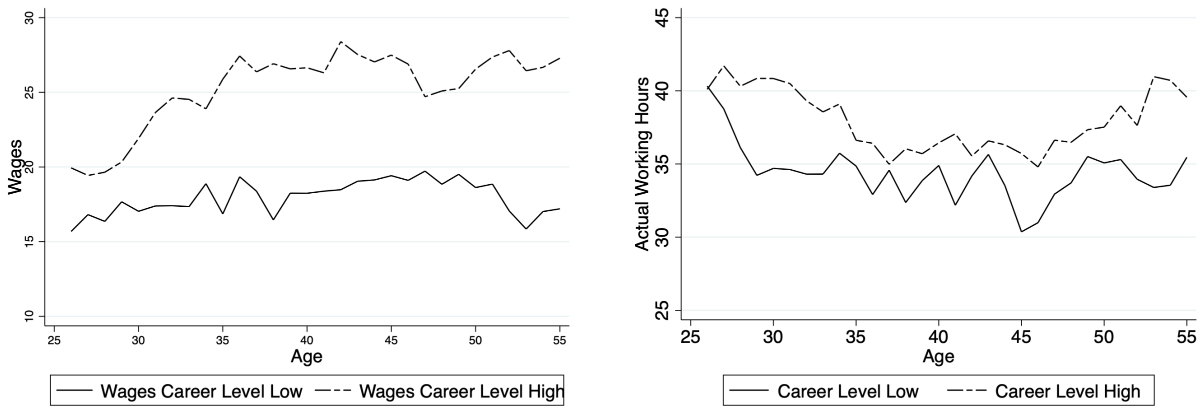

Figure 1: Age profiles of gross hourly wages and working hours by age and career level
Estimation sample. SOEP 2013-2020. Unbalanced panel of women with high education (N=3,443). Ages 26 to 55. Mean gross hourly wages by age and career level shown in panel (a). Mean working hours per week by age and career level shown in panel (b).

growth, and shorter working hours could also be driven by selection along observed and unobserved dimensions. A structural framework encompassing labor supply choices, the wage-generating process, and unobserved heterogeneity allows for estimating the causal effect of experience penalties in wage growth. Obtaining such causal estimates and performing counterfactual policy simulations motivates the structural model described in the next section of this paper.

4.2 Variance decomposition

The ability to distinguish between levels on the career ladder provides an opportunity to look at promotions as an additional mechanism that contributes to the increase in hourly wages over the life cycle. Table 4 summarizes the contributions of 4 different components to the variance in the wages earned by women who are repeatedly observed in the estimation sample. The decomposition is performed following Misangyi et al. (2006) and . It looks at individuals with different levels of full-time experience who are cross-nested in occupations and career levels within those occupations.

According to the decomposition, the highest share of the variance in repeated individual wage observations is explained by individual effects. This finding highlights the importance of accounting for individual-specific persistent unobserved factors and persistent observed states, such as the presence of children, in the structural model framework. The second most important factor in explaining the wage variance in the data is the career level. It accounts for 28.72% of the variance, thus being more informative about the wage level of the individual than, for example, the person's occupation, which explains 16.27%. The variance decomposition thus confirms the graphical result from Figure 1 in the previous subsection that wage trajectories at the two career levels differ

Table 4: Decomposition of variance in wages

Component	% explained variance
Individual effects	53.58
Career level	28.72
2-digit occupation category	16.27
Full-time experience	1.3
Residual	12.24
N	8,024

Notes: Estimation sample. SOEP 2013-2020. Variance decomposition results following Misangyi et al. (2006).

substantially. Correspondingly, the structural model features a separate wage process for each career level.

Taking the career level and the 2-digit occupation category into account, full-time experience explains only a small proportion of the variance in the wage data. This does not mean that full-time experience is irrelevant. Rather, the decomposition is consistent with the assumption that labor market engagement and tenure predict occupation sorting and career progression, which in turn determine the wage level to a significant degree. An analogous argument is made in Costa Dias et al. (2020) who conclude: "[...] our results reflect that gender differences in job sorting happen together with the expansion in the gender experience gap, as mothers taking time away from paid work fail to progress in their careers and may even move down the job ladder", p. 857. Incorporating the notion of returns to experience in wages and career progression, the structural framework I present in the next section models wage growth and promotions as a function of experience and hours worked.

4.3 Working hours choices, experience, and promotions

To gauge the existence of interactions among hours worked, the resulting experience accumulated, and promotions, I estimate a simple promotion probability model. I run a Probit regression for promotions, where an individual's probability of finding employment at the high career level is characterized by a stochastic function of a linear combination of individual full-time and part-time work experience. Experience is normalized on the $[0, 1]$ interval, where one corresponds to an individual having worked full time the entire time since she was 26, and 0 means the individual spent all years out of employment. According to the regression, there is a positive relationship between the experience level on the 0-1 experience grid and the probability of promotion. The increase is approximately linear, 2a. Correspondingly, the dependence between the probability of promotion and the full-time-equivalent stock of experience in the structural model is assumed linear.

Figure 2b shows the fraction of low career-level individuals who make a move to the high level at

(a) **Promotion Probability by Experience** (b) **Frequency of Promotions by Age**

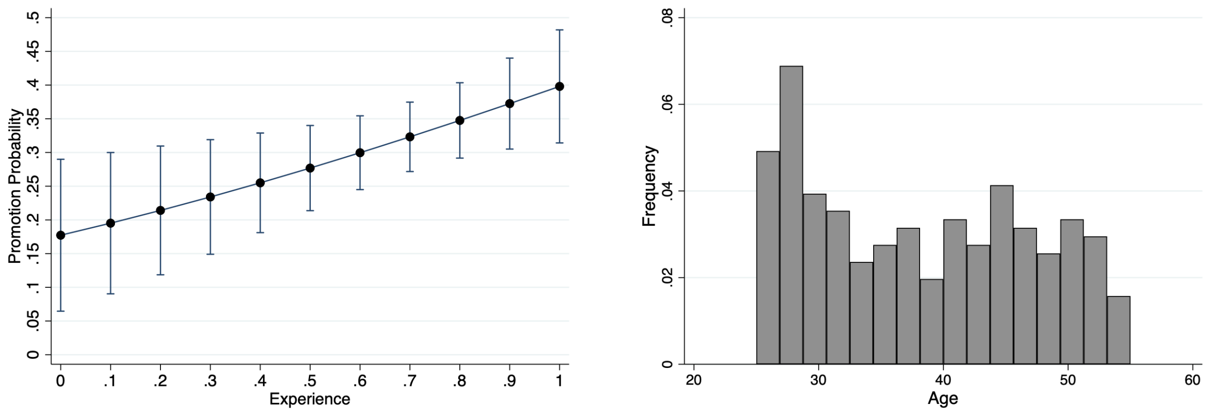

Figure 2: Promotion incidence and promotion probability
Estimation sample. SOEP 2013-2020. Unbalanced panel of women with high education (N=3,443). Ages 26 to 55. Panel (a) shows the Probit predictions of the probability of receiving a promotion given the effective stock of experience of the individual. Experience on the x-Axis is measured as full-time-equivalent years spent working as a fraction of the time in years since the individual completed education.

each age. Most upward moves happen at the beginning of the working life - between the ages of 26 and 33. After that, there is a dip in promotions, with densities increasing again in the mid-forties. This pattern is consistent with the fact that the median woman in the sample becomes a mother at age thirty. As women partly devote their early thirties to child-rearing activities, career development is halted until consistent full-time work can resume.

The structural model incorporating promotions to a higher paying level on the career ladder, differential wage equations at each career level, and the effects of children on the choice of hours of work is introduced next.

5. A life-cycle model of labor supply, human capital accumulation, and promotions

In this section, I present a model of career hierarchies to analyze the life-cycle evolution of wages as a function of individual choices of hours of work. The model's design allows me to distinguish between experience gaps that open up conditionally on the career level of a given worker, as opposed to between workers employed at different levels on a career ladder. This feature is critical for understanding the mechanisms behind the dynamic part-time pay gap based on SOEP data. It is also essential for developing policy advice based on counterfactual simulations of policies that target the promotion prospects penalty and the within-career wage penalty to differing degrees.

This section first gives a general overview of the model. Then it describes all processes in the model and discusses associated assumptions. In particular, it presents i) general assumptions; ii) the utility function and the budget constraint; iii) heterogeneity in the model; iv) the wage process and the human capital accumulation process; v) hierarchical firms and promotions; and vi) the child arrival process.

General setup Time in the model is finite and discrete. Workers are rational, forward-looking agents who decide how many hours to work from a continuum of possible choices. They solve a dynamic optimization problem, which weighs the utility of consumption against the disutility of work. The workers do not differ in their productivity, but they are heterogeneous regarding the disutility of work. This preference heterogeneity has two components, one that is unobserved and another that is observed. First, there is unobserved time-constant preference heterogeneity specific to each individual. In addition, workers of different observed characteristics experience different added disutility of work. In each period, an agent may gain a newborn child with a certain probability that depends on the person's age. Individuals have complete information and rational expectations about the stochastic fertility process. The presence of a child in a particular age group is the key determinant of the level of added observable disutility from work faced by the individual.

Wages earned in the labor market depend on the human capital an individual has accumulated in each period. They further depend on the career level of the individual. Each worker employed at the low level can receive a promotion to the high level with some probability strictly lower than one, which also depends on the individual's accumulated human capital. Crucially, the model allows for a convex relationship between the hours of work chosen in the period and the amount of human capital accumulated in that period. In other words, it allows for the possibility that working, e.g., half a work day, adds less than half a unit of human capital to the stock of the worker. By extension, within-career-level wage growth and the probability of promotion depend on the history of working hour choices. Should the individual choose not to work, she does not accumulate additional human capital in that period. She does not earn a wage but finances her consumption through the benefits she receives. These benefits depend on whether or not the agent worked the previous period, as well as on the presence of children.

Choice set Individuals enter the model after completing higher education at the age of 26. In every period for the next thirty years, each agent chooses how many hours to work. Individual wages and careers evolve until the age of 55. The workers then continue to earn the same wage they earned at age 55 for another ten years. The model ends shortly before individuals reach retirement age.

The individuals have a continuous set of choices of hours to work on the interval $[0, 48]$, which I normalize to $[0, 1]$ for computational convenience. Zero corresponds to the choice not to work; 1 corresponds to the choice to work overtime, with overtime capped at 48 hours of work per week.

For example, the choice of 0.2 corresponds to working eight hours per week[9].

Utility function I assume that the instantaneous period utility of consumption is isoelastic with constant relative risk aversion. The disutility of work is additively separable from the utility of consumption and quadratic in the hours worked as in Gicheva (2013)[10].

$$u_{itj}(h_{it}) = \frac{c(w_{itj})^{1-\eta} - 1}{1-\eta} - (F(\theta_{0p}, i) + \theta_1 X_{it})h_{it}^2 \tag{1}$$

The level of disutility that agents experience is determined by observed and unobserved factors. There are two types of individuals in terms of specific unobservables. Unobserved heterogeneity follows a χ^2 distribution with 10 degrees of freedom and a scaling factor θ_{0p}, so that $F(\theta_{0p}) = \frac{\chi^2_{10}}{\theta_{0p}}$. p denotes the unobserved disutility type.

The individual disutility of work differs along observable characteristics of an agent related to the presence and age of children. In particular, X is a vector of dummy variables indicating if, in period t, the individual's youngest child falls into one of the following age groups: 0, 1-2, 3-5, and 6 or older. The four model parameters in the vector θ_1 measure the added disutility of an additional hour of work in case a woman's youngest child falls into one of the age groups. The bins are chosen in relation to differences in child-related payments the woman may receive, the cost of childcare she faces, and the maximum amount of time the woman can devote to childcare without repercussions for her pension. A mother is eligible for motherhood replacement payments if she decides to stay unemployed in the first year after a child's birth. Childcare costs drop for children older than three years of age. A woman can spend up to three years caring for her child while still pension collecting points.

Budget constraint

$$c(w_{itj}) = w_{itj}(exp_{itj}) + T(h_{it}, X_{it}) - CHC(ch\_age). \tag{2}$$

Period consumption is the sum of the wage an individual earns on the labor market, the transfers she receives from the government, the taxes she pays, and the childcare costs she incurs. Taxes and

[9] The normalization is essential for ensuring that the range of the state variable describing the stock of experience of the worker is the same in every period. As described in the following paragraphs on the wage and the promotion processes, the relevant measure for the wages the individual earns is the full-time equivalent years of experience; the relevant measure for the probability to receive a promotion is the ratio of actual full-time-equivalent years of experience to the potential maximum full-time-equivalent years of experience.

[10] This assumption has no implications for the structural interpretation of the results. A change to a linear specification results in a change of the level of the estimated disutility parameters; it does not change the model's fit or the simulation results

transfers $T(h_{it}, X_{it})$ depend on the presence of children and the choice of hours of work. The latter determines whether an individual pays income taxes ($h > 0$), receives unemployment benefits, or receives unemployment insurance ($h = 0$).

Individuals without children who choose non-employment receive unemployment insurance in the first year and social security if not employed for longer than one year. Mothers who choose not to be employed in the first year after their child is born receive a motherhood replacement payment of 67% of the labor market wage they would otherwise have earned in the period. In addition, all individuals with a child receive a means-tested child benefit. Women with children younger than 6 incur childcare costs if they choose to work and cannot take care of the child full time. Childcare costs are assumed to be higher for children aged 0-3 and lower for children aged 3-6. There is no childcare cost incurred, once children enter school at the age of six.

Wages The log wage in the model is given by:

$$\ln w_{itj}(exp_{it}) = \delta_j + \gamma_{1j} exp_{it} + \gamma_{2j} exp_{it}^2 + \xi_{it} \tag{3}$$

$$exp_{it} = e_{it} t \tag{4}$$

$$e_{it} = e_{it-1} + \Gamma(h_{it}) \tag{5}$$

The specification in equation 3 corresponds to a Mincer (Mincer 1958) wage regression where the linear contribution of the years of education is contained in the constant $d = \ln(w_0) + \rho s$. This representation is in line with the fact that all agents have the same level of education and enter the model at the same age. The important contributor to wage formation, which differs endogenously by period and individual, is the level of accumulated experience, exp_{it}.

The wage equation specifies that wages depend on the hierarchy level at which the individual is employed: j. The wage functions of the different career levels have the same structure but differ in parameters d_j, c_{1j}, and c_{2j}.

Wages have a random component, $\xi_{it} \sim \mathcal{N}(0, 1)$. It is constant across the possible working hours arrangement the individual can choose from. The model does not feature persistent wage shocks. This modeling choice is motivated by the following two considerations. First, the period I analyze is relatively short. It considers eight years of a persistent economic upturn in Germany - from 2013, when the adverse effects of the 2008 financial crisis and the Euro debt crisis had already tapered out, until 2020, when the labor market turmoil due to the Covid-19 crisis started [11]. Wage information

[11] Proof that data from 2020 included in the sample are not yet affected by the Covid-19 recession is provided in Appendix I.

that enters the model estimation is detrended and adjusted for inflation. Second, the panel length in the sample is relatively short, with an average of 3 years. Given the limited number of occasions on which individuals are observed repeatedly, it is hard to identify permanent individual preference components and persistent individual-specific shocks. Facing this data limitation, I choose to include individual unobserved preference heterogeneity in the model.

Experience accumulation The wage-relevant level of experience in each period exp_{it}, equation 4, is measured in effective years of experience. It is a function of each individual's past choices of hours worked. The period value of this key variable is obtained by multiplying the fraction of years spent working, e_{it}, by the maximum potential experience in the respective period $e_{it_{max}} = t$.

The evolution of the effective normalized stock of experience, e_{it}, is formalized in equation 5. Effective units of experience accumulate such that individuals who choose to work less than h_{max} experience a penalty in experience accumulation in a fashion similar to Blundell et al. (2016). $\Gamma(h)$ represents a weighting function that determines what fraction of a full unit of experience is added to the experience stock depending on an individual's choice of hours worked in the current period, h_{it}. I normalize $\Gamma(0) = 0$ and $\Gamma(h_{max}) = 1$. The normalization implies that choosing not to work adds no human capital in the coming period; working the maximum amount of hours possible in the model adds one unit of human capital to the stock in the coming period.

On the interval $(0, 1)$, the chosen amount of time to work adds a fraction of a unit of experience to the next period's human capital stock. The size of the penalty for working fewer hours, $h_{it} < h_{max}$, can vary from 'no penalty', to 'zero experience added' if $h_{it} < h_{max}$. The structural assumption on the functional form of the penalty is represented by the transformation $\Gamma(.) = (y_2 - y_1)\frac{m^{(x-x_1)}-1}{m^{(x_2-x_1)-1}} + y_1$ of the line $(x_1, y_1) = (0, 0)$, $(x_2, y_2) = (1, 1)$. The key parameter in the model governing the penalty's size in experience accumulation is m. $m > 1$ implies that working less than h_{max} hours per week adds less than h to the experience stock, i.e., $\Gamma(.)$ is convex.

The dependency of the size of the penalty on m is illustrated graphically in Figure 3.

The black line, $m = 1$, corresponds to the 'no penalty' case. The absence of a penalty has been the standard assumption in the majority of research on female human capital accumulation, with the notable exceptions of Blundell et al. (2016) and Adda et al. (2017). If there is no penalty for experience accumulation, choosing to work half a day in a given period adds 0.5 units of experience to the human capital stock in the period to follow. A convexity in experience accumulation, $m > 1$, translates to an hourly wage penalty for working less than h_{max}. The value of the coefficient m governs the degree of convexity implied. For example, $m = 2$ and $m = 20$ imply a gain of 0.4 and 0.2 effective experience units, respectively.

In sum, equation 5 gives the effective, wage-relevant, stock of full-time experience equivalents in

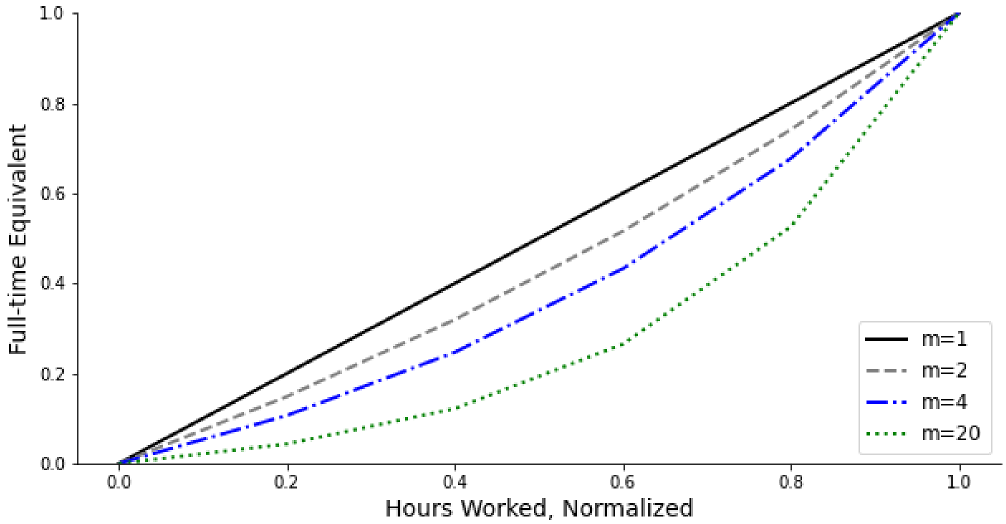

Figure 3: Degree of convexity
Full-time experience equivalents added to the human capital stock according to the size of the experience accumulation penalty as governed by m. The 45 degree line corresponds to 'no penalty'. The higher the degree of convexity of the transformation of this line, the higher the penalty.

period t normalized on the interval $[0, 1]$. An individual who has chosen to work the maximum number of hours in every period up until t has $e_{it} = 1$, while an individual who has never worked until t has $e_{it} = 0$. Correspondingly, $exp_{it} = exp_{it_{max}} = tg(h_{max}) = t$ for the former set of individuals, and $exp_{it} = 0$ for the latter.

Career levels and promotions Employment in the model is possible at two career levels. I assume that the supply of low-level jobs is fully elastic for individuals with a high level of education. This proposition results in the fact that if the wage offered at the junior career level exceeds the reservation wage of an agent, she always chooses to be employed and receives $w_{it1}(e_{it})$. Jobs at the high career level, in contrast, are assumed to be in limited supply. Employment at the high level is thus subject to constraints. The constraints manifest in that individuals employed at the low career level who would prefer high-level positions are promoted with a probability $p(e_{it})$, bounded away from one.

The promotion probability process is modeled as an increasing, linear function of the experience stock e_{it}, which tracks the fraction of time since the age of 26 each woman has spent working effectively:

$$p(e_{it}) = \pi_a + \pi_b e_{it}. \tag{6}$$

Individuals who choose to work the maximum number of hours every period have a higher chance of being promoted than those who choose to work part time or be away from the labor market. The promotion probability function is known to agents. Individuals can start their working lives at either level on the career ladder, and demotions are assumed away.

Given the assumptions of partially constrained choices, taking into account the level of disutility a worker faces, she considers two types of trade-offs when choosing her preferred working hour arrangement. First, fewer hours worked are associated with low disutility of work but will result in a lower wage in the current period and slower wage growth in the following periods. Second, with the promotion probability being an increasing function of working hours, choosing to work fewer hours implies lower chances of being employed in a high-level job.

The desirability of employment at the high level depends on level-specific wage functions. If the wage at the high career level were lower than the wage at the low career level over the entire range of exp_t, then no one would be interested in a high-level position. All employment would be at the low level, and promotion probability could not be identified. I consider this case to be empirically irrelevant. Conversely, suppose the high-level wage function dominates the low-level wage function over the entire range of years of experience. In that case, every individual will always prefer a high-level over a low-level position. As a result, all individuals wish for high-level jobs, but only a fraction will land such positions as prescribed by the promotion probability function. Finally, for specific values of the parameters, it can be the case that the portion of the population that chooses to aim for promotion is a function of individual agents' disutility in the respective period. In particular, some individuals will never be interested in promotion. Others will always prefer employment at the high career level. The final group will get a higher lifetime utility of promotion only if the event happens early enough in the life cycle. I consider the latter two cases possible empirically and apply parameter constraints in the estimation procedure, respectively.

Child arrival Child arrival in the model is exogenous. The birth of a child is a probabilistic event, and the probability of gaining a newborn depends on a woman's age. It does not depend on the number of children the woman already has. The probability distribution of child arrival is known by agents and accounted for in their decisions. The probability of child arrival is estimated from the data. It corresponds to the empirical share of newborns among women of each age. The empirical probability and the resulting exogenous probability of child arrival in the model is zero after age 44.

Maximization problem The agents in the model maximize the discounted sum of expected lifetime utilities:

$$V_t(Z_t) = \max_{\{h_\tau\}_{\tau=t,\dots,\bar{t}}} E\{\sum_{\tau=t}^{\tau=\bar{t}} \beta^{\tau=t} u(h_t)|Z_t\}, \tag{7}$$

by choosing optimal working hours h_τ conditional on state Z_t. The state space includes the age of the youngest child determined by the exogenous child arrival process and updated in a deterministic fashion if no new child is born. It further comprises the age of the individual, the evolution of which is also deterministic. The final state space components are related to the choice of hours of work and include both the level of human capital and the career level of employment. The rate at which individuals discount future utility is denoted by β.

6. Estimation

The estimation of the structural parameters of the model is performed via the Method of Simulated Moments (MSM). Before running the MSM procedure, the probability distribution of the exogenous process of child arrival and distributions governing initial conditions are estimated outside the model. This section discusses pre-set parameters, estimations performed outside the structural model, and the MSM. It offers an intuition about the identification of different sets of parameters.

6.1 Pre-set parameters

Pre-set parameters can be separated into two groups: parameters based on the fact that the empirical application concerns Germany; and parameters not specific to the German case. The latter are taken from literature, as they cannot be estimated given the structure of the model as described in the previous section and the data at hand.

The cost of childcare for children below three years of age is set at 64 Euros per week, and the cost of childcare for children aged 3-6 at 32 Euros per week, in alignment with childcare cost calculations in Geyer et al. (2015). The child benefits in the model amount to 51 Euros per week, purposefully 10 to 30% percent higher than the allowance for mothers with one child in the analysis period. I introduce a higher level of benefits to account for the fact that child benefits in the model do not depend on the number of children the way they do in reality. As most women have only one child, with very few having three or more, I consider the approximation suitable to account for the occasional presence of mothers of two children.

As far as payments for unemployment are concerned, the replacement rate for parental leave and unemployment insurance is 67%, per German legislation effective in 2022. Unemployment benefits amount to 100 Euros per week, which I view as a suitable approximation of the average benefits received across German federal states in the period I analyze.

Finally, as regards the group of pre-set structural parameters that are not specific to the German case, the discount factor β is fixed to 0.98, as in Blundell et al. (2016). The coefficient of the degree of relative risk aversion η is set to 1.1, thus introducing risk aversion in the model only to a mild degree. I refrain from setting the parameter high because strong concerns about risk may affect labor supply choices too heavily. As savings are assumed away, it represents the only channel that agents can use to ensure against risk.

6.2 Exogenous process and initial conditions

Child arrival is assumed to be exogenous in the model. The probability that a child will arrive is set equal to the empirical frequency of births given a woman's age in the data. Figure 4 shows the distribution of child arrival probabilities by age of the mother (Panel (a)) and the evolution of the proportion of women who have become mothers over the life cycle (Panel (b)). The highest probabilities of child arrival correspond to ages 30 and 37, with a peak of over 14% at 32. The probability decreases abruptly after the age of 37. Finally, the number of mothers stops growing at age 44. The probability of child arrival for individuals older than 44 is set to zero[12].

(a) **Probability distribution of child arrival** (b) **Simulated share of mothers**

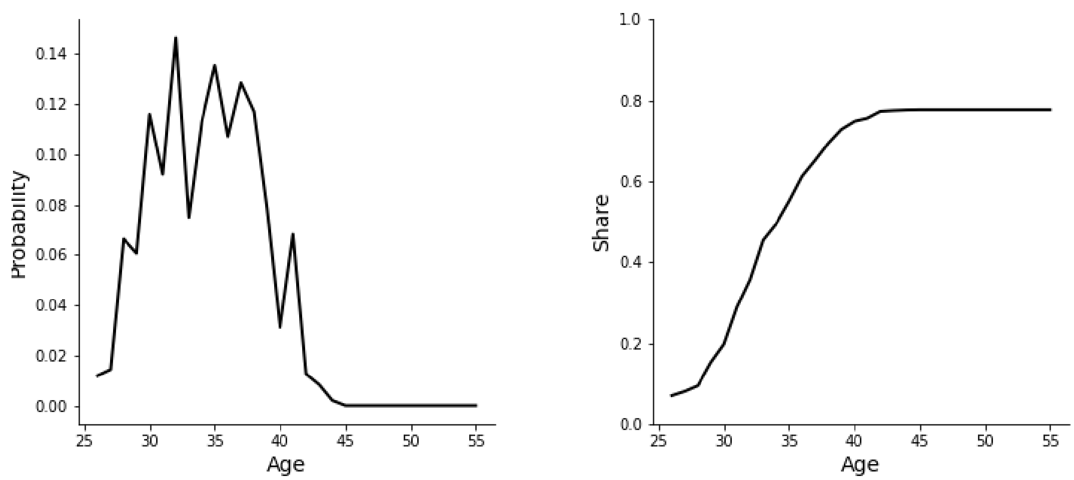

Figure 4: Exogenous child arrival process
Panel (a) shows the probability distribution that agents in the model take into account when building an expectation about child arrival in the period given their own age. The probabilities correspond to the observed shares of newborn children by age of mother in the estimation sample. Panel (b) plots the share of mothers in the simulated sample that results from newborn children arriving according to the probability distribution in Panel (a).

Individuals can have children born before entering the model at age 26. This is the case for ca. 8% of women in the SOEP sample. The distribution of the ages of the youngest children in the first

[12]Childbirth does not occur after 44 years of age in the model, as the few women who give birth at a higher age according to the SOEP are not included in the sample.

period of the model equals the empirical distribution of the ages of the youngest children among individuals aged 25 in the data.

The estimation sample includes only women with high education. The number of years of education is not a choice variable in the model. Thus, the level of education can be viewed as an initial condition. Individuals can start their working lives at either level of the career ladder. I let as many individuals enter the model at the high level as match the proportion of high-level employees at age 25 in the SOEP estimation sample. Beyond the year of labor market entry, I assume that a promotion to the high career level is not possible without prior work experience, $\pi_a = 0$.

6.3 Structural parameters

6.3.1 Method of simulated moments

I estimate the model using indirect inference. Intuitively, I use the method of simulated moments to choose a vector of parameters to minimize a criterion function representing distance. The criterion function measures the weighted distance between a collection of moments from the observed data and their counterparts from a data set simulated using the specified model. The moments summarize the essential aspects of individual decision-making and behavior in the data and inform the identification of the model's parameters.

Formally, let ω denote the collection of parameters to be estimated in the MSM procedure. Then, the indirect inference estimator of ω is given by:

$$\widehat{\omega} = \underset{\omega}{\operatorname{argmin}} \left(\widehat{mom\_obs} - \widehat{mom\_sim}(\omega)\right)' \Sigma \left(\widehat{mom\_obs} - \widehat{mom\_sim}(\omega)\right), \tag{8}$$

where $\widehat{mom\_obs}$ denotes the vector of moments related to the behavior observed in the estimation sample and $\widehat{mom\_sim}(\omega)$ denotes the vector of moments calculated based on simulated data from the life-cycle model with parameter values ω.

The minimization problem is based on the weighted squared difference of the moments with a diagonal weighting matrix, Σ. I obtain an estimator of the optimal weighting matrix, $\widehat{\Sigma}$, by bootstrapping the variance of the observed moments. $\widehat{\Sigma}$ is a diagonal matrix containing the standard deviation of each moment on the diagonal[13].

Standard errors of the estimated parameters correspond to the elements on the square root of the diagonal of the variance-covariance matrix:

[13] Details regarding the implementation of the estimator are provided in Appendix VI.

$$(\widehat{D}'\widehat{\Sigma}\widehat{D})^{-1}\widehat{D}'\widehat{\Sigma}\widehat{\Omega}\widehat{\Sigma}\widehat{D}(\widehat{D}'\widehat{\Sigma}\widehat{D})^{-1}, \tag{9}$$

with

$$\widehat{D} = \frac{1}{2} \left. \frac{dM(\omega_l)}{d\omega_l'} \right|_{\omega_l=\omega} \tag{10}$$

Simulated moments are denoted M. Ω is the variance-covariance matrix of observed moments. $\hat{\Omega}$ is estimated by the same bootstrapping procedure as $\widehat{\Sigma}$.

6.3.2 Moments and identification

The estimation procedure uses 115 moments that describe the behavior of females at both levels of the career ladder, given their observable characteristics as well as the wages they earn. The moments can be calculated given the information available in the SOEP estimation sample as described in Section 3 and also from data simulated using the model described in Section 5.

Establishing the identification of each of the model's parameters formally is challenging. In the following, I provide a heuristic identification argument for each parameter group by discussing the variation in the data that inform the value of each respective parameter. First, wage equation parameters are associated with empirically observed evolution in wages. In particular, constants are strongly related to wages earned at the beginning of the life cycle, when individuals are just starting to accumulate job-relevant experience. The returns to experience are, in turn, determined by wage gains due to working the maximum number of hours possible. The degree of convexity of experience accumulation, m, is driven by the downward deviation in wage gains when working fewer than the maximum number of working hours. The vector of moments used in the MSM procedure includes log wages by the level of experience and log wages by a woman's age at both levels of the career ladder to capture the identifying variation in wage parameters.

Second, disutility parameters are associated with individual choices. The observed disutility component θ_1 is strongly related to the working-hour choices of individuals with respective X_i. The unobserved component of the disutility, θ_0, drives the working-hour choices of workers with baseline X_i given specific career levels. The moments used to describe the relevant variation in choices include average working hours by the youngest child's age and the fraction of individuals with a child in each age group, as specified in Section 5, choosing different numbers of working hours. Importantly, choice moments and wage moments, while most likely primarily associated with a disutility and a wage parameter, also inform other parameter groups via selection mechanisms and dynamic human capital accumulation. Choices are related to the level of wages; conversely, wages are related to the level of experience, which is the product of past choices.

Finally, the probability of promotion is informed by the number of promoted individuals, the ratios of promotions given the history of working-hour choices, and working-hour choices unexplained by the wage equations.

7. Results

This section presents estimation results based on the structural model and SOEP data. It discusses parameter estimates and the decomposition of the wage penalty; in specific to what it extent it can be attributed to i) a within-career-level component versus ii) a between-career-level component.

7.1 Parameter estimates

Table 5 presents the parameter estimates from the endogenous model coefficients obtained through the MSM procedure.

Wage process The estimated empirical structural model offers insights into wage dynamics at the two different levels of the career ladder. These are critical inputs into decisions that modeled individuals make. While some patterns of interest are harder to quantify without the help of additional calculations, several interesting conclusions can be drawn directly from the parameters of the wage equations.

The first key finding concerns the level of constants in wage processes. They are structurally related to the earnings of individuals, as predicted by occupation level, without a history of work experience. Having taken selection into account via the model's structure, the baseline earnings at the high career level are estimated to be higher than those at the low career level: $\delta_2 = 2.732$ and $\delta_1 = 2.653$, respectively. Some micro-theoretical applications, e.g., Gicheva (2013), assume that without much relevant work experience, individuals in simple junior jobs can still have relatively high earnings, while advanced senior jobs pay more if workers are already experienced. I do not find support for this claim in the data at hand. In contrast, conditional on having completed tertiary education, starting wages are higher in the more complex and more demanding high career level jobs.

The second central finding is related to estimated returns to experience accumulation. The linear component of returns to experience is markedly higher at the high career level - $\gamma_{12} = 0.161$ versus $\gamma_{11} = 0.042$. These generous experience rewards drive the steep wage increases enjoyed by young individuals at the high level. Still, the convexity of experience accumulation, $\gamma_{22} = -0.008$, is also much more pronounced at the high career level. Correspondingly, the more human capital an individual has already accumulated, the less attractive it is to collect further experience on the job, as the convexity in returns kicks in.

In sum, wages at the high career level dominate wages at the low career level over the entire range of the experience distribution[14]. A promotion is, thus, desirable for all agents in the model. It is optimal at every stage of the life cycle regardless of the level of the disutility of work that an individual faces. Promotions into the high career level permanently transfer workers to a higher wage trajectory.

Table 5: MSM Estimates of structural model parameters

Group	Parameter	Description	Value
Wage equation	δ_1	constant level low	2.653 (0.002)
	δ_2	constant level high	2.732 (0.001)
	γ_{11}	linear exp. term level low	0.042 (0.000)
	γ_{12}	linear exp. term level high	0.161 (0.000)
	γ_{21}	quadratic exp. term level low	-0.002 (0.000)
	γ_{22}	quadratic exp. term level high	-0.008 (0.000)
	m	degree of convexity exp. accum.	2.166 (0.008)
Heterogeneity unobs.	θ_{01}	scaling factor type low	42.362 (1.748)
	θ_{02}	scaling factor type high	47.112 (3.173)
	$prob_{low}$	probability low type	0.428 (0.000)
Heterogeneity obs.	θ_0	disutility child age 0	-0.032 (0.000)
	θ_2	disutility child age 1,2	2.939 (0.006)
	θ_3	disutility child age 3, 4, 5	1.186 (0.001)
	θ_4	disutility child 6 or older	0.010 (0.000)
Promotions	π_b	promotion probability slope	0.063 (0.000)

Notes: Estimates of the structural parameters of the model presented in Section 5 based on the SOEP estimation sample discussed in Section 3. MSM estimation based on 115 moments. Estimates rounded to three digits. Standard errors in parenthesis.

[14]This statement considers both the linear and the squared terms in wage processes, eq. 3. This holds true in the presence of part-time penalties as estimated using the SOEP sample and in the absence of a part-time experience accumulation penalty, i.e., if convexity in experience accumulation is assumed away.

Utility function The estimated parameters of the utility function comprise the contributions of observed and unobserved characteristics to the disutility of work. As regards the the two unobserved heterogeneity types θ_{01} and θ_{02}, estimates suggest that there is a relatively small difference in the disutility of work between them which suffices to produce significantly different choice paths. 42.8% of individuals are estimated to belong to the 'low type' group.

Individuals differ more strongly in the level of disutility they experience, as predicted by observables. The baseline level of disutility is assigned to individuals without children. Compared to the baseline group, disutility associated with the presence of children is highest for children aged one to two and decreases with the increasing age of the youngest child. Individuals whose youngest child is already in school - six years old or older - have almost the same disutility of work as the group of individuals who do not have a child, with $\theta_4 = 0.010$. At first glance, the parameter on newborn children seems at odds with the general pattern in the group of observed heterogeneity parameters. It is estimated to be the lowest of the group, $\theta_0 = -0.032$. The estimate is explained by the financial transfers mothers receive in the first year after childbirth. The transfer function in Germany is generous, replacing 67% of a mother's net labor income in the year before birth, with a cap at 1,800 Euros per month. This transfer, plus the child benefits the mother receives in addition, is estimated to overcompensate young mothers, who work around eight hours per week on average, maintaining their labor market attachment even in the presence of newborn children.

Promotion process The slope of the promotion probability function on the interval $[0, 1]$ is estimated at 0.063. This corresponds to a promotion probability of 4.5% for an individual working $0.5 * h_{max}$ in the first year after completion of education. The promotion probability of a worker choosing to work h_{max} hours is around 2% higher.

I now turn to a discussion of the implications of the estimation results for the the part-time penalty in experience and wages and its decomposition.

7.2 Part-time penalty in experience accumulation

The part-time penalty in experience accumulation in the model is determined by the degree of convexity of the experience accumulation function $\Gamma(h_{it})$. The convexity parameter m equals 2.116, which implies that working 24 hours a week increases one's experience stock by ca. 0.42 full-time equivalence units. As a comparison, Blundell et al. (2016) estimate that depending on the level of education, working part time adds only 0.15 units of a full-time experience equivalent to the human capital stock of a worker. The difference in the result is directly related to differences in model design. In the absence of career levels, a wage increase following a promotion is interpreted as a wage increase following directly from the accumulation of human capital. When experience accumulation is assumed to determine the probability of promotion, a significant part of observed wage growth is attributable to the increase in the probability of promotion to the higher-paying high career level. Consequently, introducing promotions into the model results in lower experience penalty estimates. This, however, does not mean that part-time penalties are lower. Only, to asses the size of the part-time penalty in the model at hand the convexity in the accumulation of experience has to be evaluated together with the respective returns to experience at either level and the probabilities for promotion given the stock of experience of the model agent.

The implications for policy of the varied dynamics of the part-time penalty in experience in the presence of hierarchical wage structures and promotions are discussed in Section 8. In the remainder of this section, given the parameters of the wage generating processes on both career levels and the estimate of the part-time penalty in experience accumulation, I quantify the wage penalty that a typical individual experiences, and the decomposition of wage stagnation due to part-time work in terms of *i) a promotions penalty* component and *ii) a within-career-level penalty component.*

7.3 Dynamic implications of the part-time penalty in experience accumulation

7.3.1 Median individual part-time penalty

To ease exposition, I evaluate the size of the wage penalty in the model framework with promotions for an individual who reduces her working hours for two consecutive years starting at age 31. I assume that the individual worked 40 hours a week between the ages of 26 and 30 and then spent a year not working following the birth of a child. This trajectory corresponds to a pattern commonly observed in the data; thus, I call the model agent the 'median individual'[15]. Next, to measure the total part-time wage penalty, I compare the part-time wage trajectory of the worker with the wages she would have earned had she returned to work full time. Finally, I focus the following arguments on full-time work, defined as $h = 40$, and part-time work, defined as 50% of full-time, $h = 20$. In this way, I can ensure comparability with the body of previous literature that analyses part-time employment, assuming that part-time work amounts to working half a day, or around 20 hours per week. I then comment on the comparative statics for other part-time working arrangements, e.g., 8 hours per week, leveraging the continuous choice specification in the model.

At 33, the median individual earns 22.00 Euros per hour. This amount corresponds to hourly wages at low and high levels weighted by the probability that the worker received a promotion given her history of working-hour choices. In comparison, she would have received 22.92 Euros per hour if she had returned to work full time after the employment interruption. This implies a penalty of 96 Euro Cents or ca. one Euro per hour[16].

The one Euro penalty is the gap between full-time and part-time trajectories for the median individual after two years of part-time work. It is the sum of hampered wage growth conditional

[15] In this analysis I integrate over all stochastic elements in the model, but the arrival of the first child; it is assumed the model woman becomes a mother at age thirty.

[16] Or appx. 4% of the full-time trajectory wage.

on career level and forgone chances of promotion. The penalty is more considerable if part-time employment consists of fewer than 20 hours of work per week. For example, if the woman chooses to work only 8 hours per week, the hourly wage penalty at age 33 would be 1.39 Euros. The reverse is true if working hours are more than 20. The penalty grows larger the longer the worker stays on a part-time trajectory - the faster the less the woman chooses to work.

The question of primary interest in this paper – how to describe the penalty in terms of i) a penalty in opportunities to be promoted and ii) a penalty in wage growth conditional on the career level - is discussed next.

7.3.2 Within-career-level penalty

(a) **Career level low** (b) **Career level high**

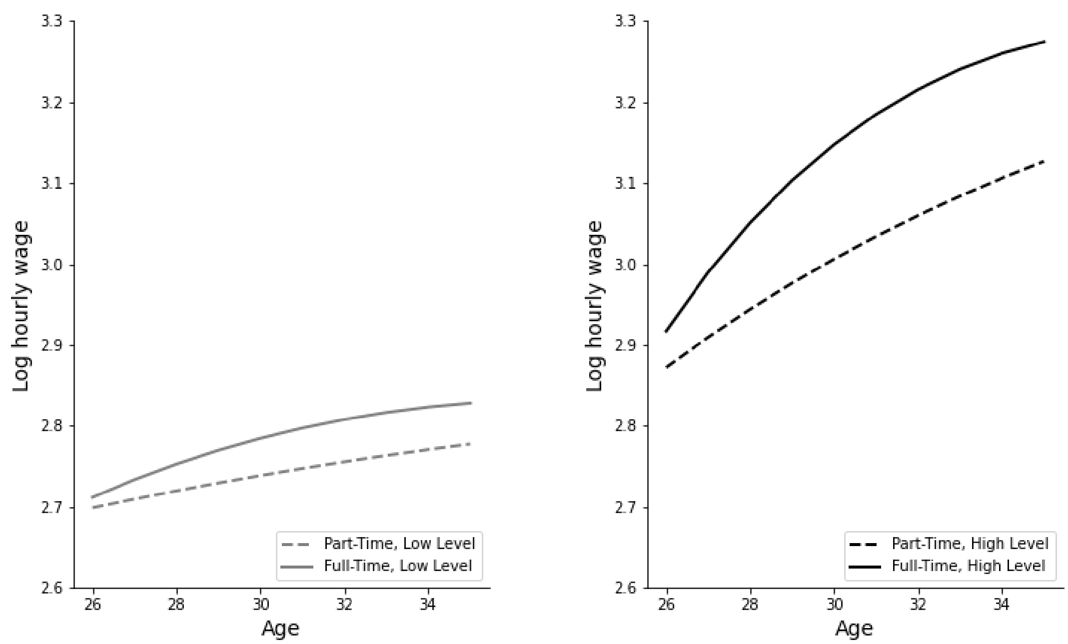

Figure 5: Part-time wage penalties by career level
Panel (a) shows the trajectories of hourly wages for employees at the low career level. Solid lines indicate full-time workers, while dashed lines represent part-time workers. Full time corresponds to 40 hours of work per week; part time corresponds to 24 hours of work per week. In an analogous fashion, panel (b) plots the hourly wage trajectories for full-time and part-time workers at the high career level.

Figure 5 shows the wage trajectories for full-time and part-time workers at both career levels, as the empirical structural model implies. The graph provides a visualization of the relative size of the part-time penalty within each level. The average hourly wage penalty over the first ten years of the life-cycle amounts to 0.66 and 2.82 Euros per hour, or 4.10% and 12.17%, at the low and high levels, respectively. The penalty for working half a day is around three times larger at the high career level.

At first glance, this within-level-penalty pattern is less visible when looking at cumulative gross earnings for the two career levels. Earnings on the part-time trajectory appear much lower than suggested by the hourly wage penalty. This result is due to the mechanical loss of earnings in part-time employment: part-time workers earn only half as much as full-time workers, even without penalties, simply because they spend less time working. Therefore, earnings calculations need to be adjusted for the difference in working hours on the two trajectories. The adjusted penalty in gross yearly labor earnings amounts to 5,423 Euros per year at the high career level and 1,273 Euros per year at the low career level. The latter is approximately three fifths the size of the monthly minimum wage pay in Germany[17].

The fact that the within-career-level penalty is lower at the low career level is closely related to the finding that wage growth at the low career level is limited, even for workers who accumulate experience fast. The wage profile at the low career level is generally flat. Low returns to experience, in turn, induce optimality of part-time work. In sum, lack of wage growth at the low career level is the consequence of both low returns and slow experience accumulation. Working long hours cannot entirely help one escape the low-wage trap at the low career level. Earning low wages is best avoided by moving to a high career-level job.

7.4 Part-time penalty decomposition

In this section, I add in the dimension of the penalty for foregone promotions. For the analysis, I again look at the median individual example. I assume that at age 31, she is still employed at the low career level. I trace her path in two scenarios: i) she chooses to work full time, $h = 40$, over the next four years, or ii) she chooses to work part time, $h = 20$, over the next four years[18].

At age 35, the gross labor earnings of the individual, cumulative over the four years, amount to 171,655 Euros on the full-time and 162,175 Euros on the part-time trajectory, respectively[19]. The implied total penalty is 9,480 Euros or 2,370 Euros per year. The amount part-time workers lose in a year is thus comparable with average net monthly earnings at the high career level. On top of earning half the amount full-time workers earn due to working 20 hours a week, part-time workers are additionally penalized by the equivalent of a month's wages per year.

In order to juxtapose the wage losses due to forgone chances at promotion against the within-level

[17] As of October 2022 the minimum hourly wage in Germany is 12 Euros per hour, which yields approximately 2,160 Euros gross monthly assuming the individual works 40 hours per week for 4.5 weeks a month

[18] The choice to analyze a four-year-long spell will become apparent shortly.

[19] Part-time calculation adjusted for the mechanical effect of working lower hours.

wage penalty, I simulate the average earnings trajectory of the worker in the part-time scenario while setting the probability of promotion equal to the probability of promotion in the full-time scenario. Adjusting for the difference in promotion chances, I find that 55% of the overall penalty can be explained by the forgone possibility of promotion. If individuals on the part-time trajectory faced the same probability of promotion as full-time workers, their average gross earnings would amount to 167,356 Euros over four years. The career prospects penalty dominates more strongly the longer a part-time spell lasts. For short part-time spells, the larger part of the penalty is attributable to wage losses within level. As discussed in the previous subsection, these are generally higher at the high career level. If part-time work comprises less than 20 hours per week, the break-even duration of the part-time spell is shorter than four years. In sum, for short career interruptions, both factors are roughly equally important in explaining the part-time wage gap. The longer the part-time spell, the more critical the promotion penalty becomes.

These results have important implications for for the efficacy of policy interventions. In particular, policies can be successful in reducing part-time experience gaps and related wage gaps to a different degree, depending on the part of the population they target and on the period of one's working life they influence. The next section discusses two policy simulation and illustrates how they affect individuals' choices of hours of work and wages in promotions in the model, respectively.

8. Counterfactual analysis

The results discussed in Section 7 suggest that both processes – foregone promotions and within-level wage stagnation - are relevant in explaining the part-time wage gap. In this section, I demonstrate that analyzing the differential impact of part-time work on wage growth within career levels and on promotion prospects between levels is pivotal for policy design. I perform two counterfactual simulations that model two different ways in which policymakers may aim at reducing the part-time wage gap. Both policies increase individuals' overall earnings from employment, with different parts of the population that react to the policy change the most. However, neither policy leverages the promotion channel. As the analysis will show, measures specifically targeted at stimulating career development early on in the lifecycle can be a suitable complement to both policies I simulate. Financial incentives which increase working hours and policies which ensure that experienced workers advance in their careers are both essential ingredients in an effective policy mix.

8.1 Child care costs

The first policy I analyze envisions reductions in the cost of childcare. As families in Germany rely to a significant degree on the government's childcare provision, the cost of sending children to a nursery or a kindergarten is a key topic in the policy debate. A reduction in the cost of day care is expected to increase the labor market attachment of mothers of small children and increase the time individuals spend working.

Using the structural framework and the parameter estimates discussed above, I perform a counterfactual simulation where childcare costs for children aged 0-2 and 3-6 are decreased by 10%. As anticipated, the new regime induces longer working hours. The increase is particularly pronounced at the beginning of the life cycle for ages 26-30 and at the end of the lifecycle, for ages 45-55. On average, increases in the intensive margin of labor supply amount to 1.75 hours of work per week, or 5.8%. They translate into a 6% increase in lifetime earnings from employment. The size of the effect amounts to 59,017 Euros gross, or around 1.5 years' wages. However, the increase in hourly wages is markedly lower. These increase by 9 cents per hour, corresponding to 0.41% of the average wage.

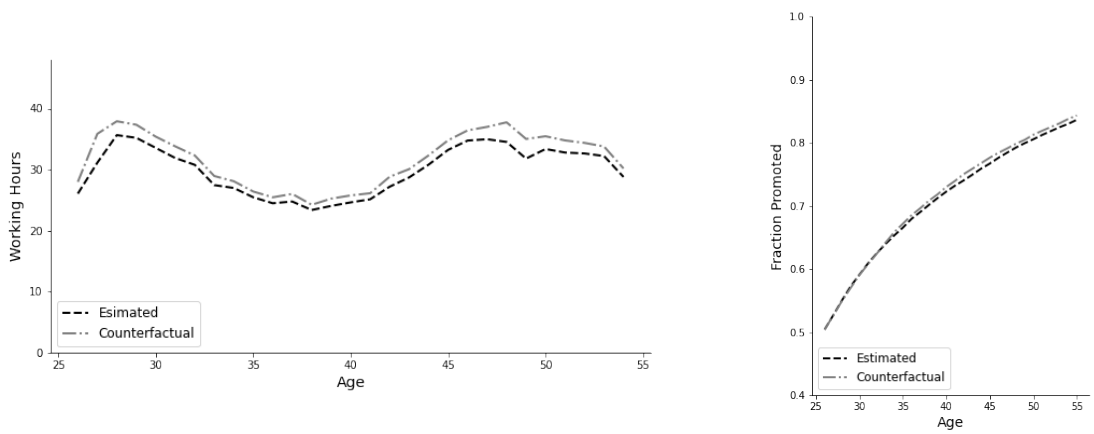

Figure 6: Lifecycle profiles of working hours and promotions with reduced cost of childcare
Dash-dot lines indicate simulated trajectories from a counterfactual scenario with reduced childcare costs by 10%, while dashed lines correspond to the trajectories in the model estimation using the SOEP data. The left panel shows the lifecycle profile of working hours chosen by the agents in the respective model. The right panel shows the stock of promoted individuals by age.

The positive change in lifetime earnings induced by reduced childcare costs is mainly driven by the mechanical effects of the increase in working hours rather than by a mitigation of the part-time penalty. Part-time penalties are mitigated only to a small degree for two main reasons. First, the effects of the proposed on young individuals mostly affect women who choose not to work at all or to work very few hours in the status quo regime. The generated increase in working hours does not suffice to reduce within-level wage gaps significantly. Second, as depicted in the right panel of Figure 6, the increase in working hours among the 26-to-35-year-olds does not result in more promotions. An increase in promotions is only triggered by the increased time spent working by older individuals. Notably, as promotions happen at a later stage of the lifecycle, the monetary gains of switching to a higher pay grade are limited.

8.2 Tax reform

The second policy I evaluate intends to treat all women, i.e., it does not target mothers only. It implements a proportional reduction of the income tax for everyone working. The amount of the reduction is such that the average income tax rate employed individuals in the model face is thirty percent.

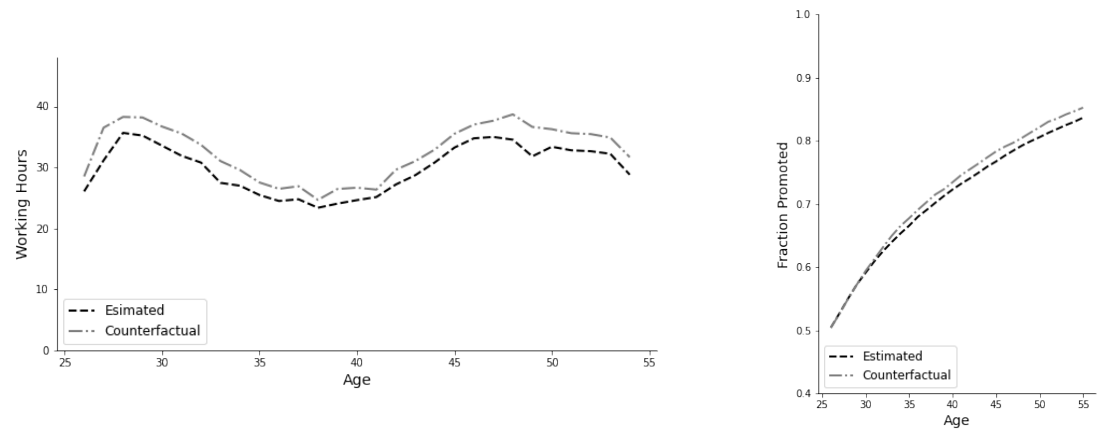

Figure 7: Lifecycle profiles of working hours and promotions with reduced income taxes
Dash-dot lines indicate simulated trajectories from a counterfactual scenario with reduced income taxes, while dashed lines correspond to the trajectories in the model estimation using the SOEP data. The left panel shows the lifecycle profile of working hours chosen by the agents in the respective model. The right panel shows the stock of promoted individuals by age.

Figure 7 shows the effects of the policy on working hours and the fraction of promoted individuals by age. Comparing the left panels in Figures 6, and 7, it is visible that the tax reform induces a higher increase in the number of hours agents in the model chose to work. Averaging over all periods and individuals in the model, working hours increase by 2.7 per week. The increase is stronger at the beginning and toward the end of the lifecycle than for ages 35-45. The differences are less pronounced than under the reduced childcare costs scenario. Lifetime earnings from employment increase by 10%.

High earners profit most from the reform. In line with this incentive, the increase in hours worked is driven by women who worked 32 hours or more in the baseline scenario and chose to work full-time or even overtime when taxes are reduced. Women without children comprise the largest share of the individuals who respond to the tax reform by altering their choice of work hours. Thus, the tax reform benefits a different part of the simulated sample of women as compared to the childcare cost reform. Because of this, an increase in promotions can be observed several years earlier; see the right panel of Figure 7. However, the effect on promotions in the second counterfactual simulation remains modest. The number of individuals employed in a high career level job increases by 1.5

percentage points.

8.3 Policy discussion

The counterfactual analysis shows how different policies can have similar results while affecting different parts of the population. At the same time, the effectiveness of policy actions aimed at decreasing pay gaps can be improved if measures leveraging the promotion channel are added to the policy mix.

What is common to both counterfactual scenarios analyzed in this section is the lack of additional promotions at the beginning of the lifecycle, ages 26-32. The reason for this is that even in the baseline scenario, the number of individuals eligible for a promotion exceeds the number of workers who can be promoted. While under both alternative policy regimes, the number of young workers eligible for a promotion increases - more significantly so in the counterfactual featuring reduced income taxes - there is no effect on the share of high career level workers because jobs at the high career level attainable by women are rationed. While each policy might benefit certain women individually (in case they become eligible for a promotion and receive it instead of someone else), neither policy leverages the promotion channel explicitly.

Correspondingly, a policy mix that increases hours worked and leads to more female employment in high career-level jobs can be more effective in combating the dynamic part-time wage gap than a monetary incentive to work more alone. Such combined policy intervention will induce not only higher earnings but also close gaps in wages and female representation at the high rungs of the career ladder. The latter can have spillover effects that benefit the individual and the economy as a whole additionally. For example, the more women with successful careers, the more role models and the greater the diversity and agility in leadership styles.

Importantly, the childcare cost and the tax reform can profit from the paralleled introduction of another policy that ensures more qualified young women are promoted. Similarly, measures that increase the chances of a promotion for women, such as mentoring programs, equality of opportunity rules for HR selection procedures, or quotas, will benefit from simultaneously creating monetary incentives to increase working hours. In the model, an increase in the availability of high career-level jobs is likely to result in individuals increasing their labor input when young and decreasing the number of hours they work in their forties and fifties. If a promotion happens early on, full-time work is encouraged only up to a point because the returns to full-time employment increase at a decreasing rate. Consequently, stagnating wage growth in demanding high career-level jobs might result in demotions and thus have adverse consequences for lifetime earnings from employment. Therefore, a complement of policies ensuring both strong labor market attachment and fast career progression would be necessary to close the part-time experience gap effectively.

9. Conclusion

In this paper, I study the relative importance of the lack of promotions and lack of within-career-level wage growth in explaining the part-time wage gap over the life cycle of female employees. First, I introduce a career ladder and the notion of promotions to higher-paying career levels in the dynamic life-cycle framework of Keane & Wolpin (1997, 2010). Second, I quantify the contribution of each separate channel to the part-time penalty for highly educated women using data from the SOEP survey for 2013-2020. Finally, based on the proposed model and its empirical estimation, I present counterfactual evidence that illustrates the relative degrees of effectiveness of two possible reforms that could combat the part-time wage gap - a reduction in childcare costs and income taxes.

The life-cycle analysis in the promotion framework reveals the strong effect of promotions on wages and lifetime earnings. This is because wage trajectories at the two career levels are estimated to differ substantially: returns to experience are steep at the high career level and almost absent at the low career level. Findings show that part-time employment triggers both within-level wage penalties as well as penalties for the probability to be promoted. Wage growth penalties within level are transmitted through a slowdown in experience accumulation while working part time. Given the unequal returns to experience at both levels, the within-level penalty at the high level is approximately three times higher than at the low level.

The part-time penalty for receiving a promotion is a product of the penalty in human capital accumulation and the positive dependence between the probability of being promoted and the level of human capital. The part-time spell length of four years marks the point at which forgone chances of promotion and within-level wage losses contribute to the overall penalty due to part-time work to an equal degree. For longer periods of part-time employment, the higher share of the long-run part-time penalty accrues to foregone opportunities to be promoted.

The policy analysis I perform using the estimated life-cycle model shows that a reduction in the cost of child care or in income taxes can generate increases in wages and lifetime earnings from employment. However, each policy affects a different part of the population and benefits mothers or high-earners deferentially. Neither reform increases the fraction of high-career-level workers substantially. The effectiveness of policy actions aimed at decreasing pay gaps can, therefore, be improved if measures leveraging the promotion channel are added to the policy mix.

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Appendix

Appendix I: Data 2013-2019 and Data 2020

Table SWA.1: Descriptive Statistics 2013-2019

	Mean/Share	Median	S.D.	Min	Max
Age	39.25	38.00	8.58	25.00	55.00
Number of Children in Household	0.69	0.00	0.93	0.00	7.00
Contractual Working Hours	33.60	38.00	8.42	2.00	70.00
Overtime Hours	2.18	1.00	3.05	0.00	23.00
Gross Hourly Wage	22.93	21.46	8.91	8.36	59.21
Employment Status					
Non-Working (%)	0.18	0.00	0.38	0.00	1.00
Part-Time (%)	0.30	0.00	0.46	0.00	1.00
Full-Time (%)	0.52	1.00	0.50	0.00	1.00
Promotion to Senior	0.11				
Motherhood	0.57				
Age at first Child	29.80				
Individuals	3318				

Notes: Estimation sample. SOEP 2013-2019. Unbalanced panel of women with high education (N=10,886).

Table SWA.2: Descriptive Statistics 2020

	Mean/Share	Median	S.D.	Min	Max
Age	38.70	37.00	8.20	25.00	55.00
Number of Children in Household	0.80	0.00	0.98	0.00	6.00
Contractual Working Hours	33.28	38.00	8.19	8.00	48.00
Overtime Hours	1.72	1.00	2.37	0.00	19.00
Gross Hourly Wage	23.91	22.77	8.11	8.62	59.20
Employment Status					
Non-Working (%)	0.16	0.00	0.37	0.00	1.00
Part-Time (%)	0.34	0.00	0.48	0.00	1.00
Full-Time (%)	0.49	0.00	0.50	0.00	1.00
Promotion to Senior	0.15				
Motherhood	0.57				
Age at first Child	30.10				
Individuals	1456				

Notes: Estimation sample. SOEP 2020. Unbalanced panel of women with high education (N=1,456).

Appendix II: SOEP Survey item

Salaried employee engaged in unskilled activities *(Angestellter mit einfacher Tätigkeit)*

– without completed training / education .. ☐

– with completed training / education .... ☐

Salaried employee engaged in skilled activities (*Angestellter mit qualifizierter Tätigkeit)* (e.g., executive officer, bookkeeper, technical draftsman).................................. ☐

Salaried employee engaged in highly skilled activities *(Angestellter mit hochqualifizierter Tätigkeit)* or managerial function (e.g., scientist, engineer, department head, Industry or factory foreman / forewoman) .. ☐

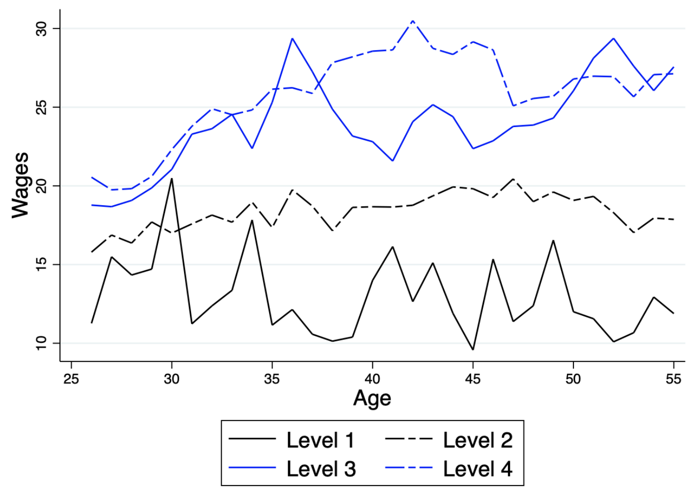
Salaried employee with extensive managerial duties *(Angestellter mit umfassenden Führungsfunktion)* (e.g., managing director, business manager, head of a large firm or concern) .. ☐

Figure SWA.1: SOEP survey item for classification of job on 4-level vertical scale

The figure shows the SOEP survey item which facilitates the classification of the job of each salaried employee on a vertical scale with 4 levels - i) unskilled activities, ii) skilled activities, iii) highly skilled activities, iv) extensive managerial duties - according to the degree of skill required, and the complexity and responsibility for personnel involved.

Appendix III: Career levels

(a) Wage Profile by Job Level



(b) Working Hours Profiles by Job Level

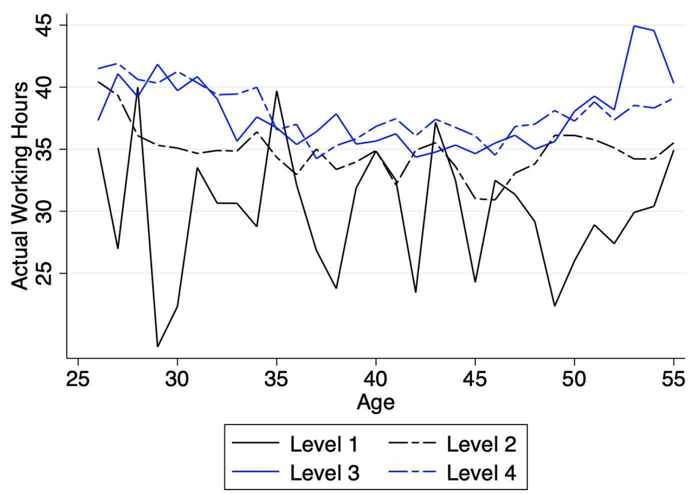


Figure SWA.2: Wages and working hours, 4 career levels

The figure shows how hourly wages and working hours vary by age and career level. The plot distinguishes between 4 career levels as recorded in the SOEP data and described in Section 3. Panel (a) shows hourly wage profiles by age. Panel (b) shows weekly working hours as specified in the working contract by age.

Appendix IV: Variance decomposition

To decompose the variance in the repeated individual wage observations I estimate a series of regression equations by maximum likelihood as proposed by Misangyi et al. (2006) and Hough (2006). The multi-level regression model posits that the wages of each individual who appears multiple times in the panel dataset, w_{tij}, vary around a person specific mean a_{0ij}, a mean for wages at the respective career level of employment β_{00j}, and an overall sample mean γ_{000}.

$$
\begin{aligned}
w_{itj} &= a_{0ij} + e_{itj}, && e_{itj} \sim N(0, \sigma_e^2)\\
a_{0ij} &= \beta_{00j} + u_{tj}, && u_{tj} \sim N(0, \sigma_u^2)\\
\beta_{00j} &= \gamma_{000} + v_j, && v_j \sim N(0, \sigma_v^2)
\end{aligned}
\tag{11}
$$

Given the above model, to compute the contributions of a) individual specific effects, b) career level effects, c) occupation effects, d) experience effects, and e) residual effects, I estimate the equations above as well as the auxiliary regressions:

$$
w_{tij} = a_{0ij} + a_{1ij} Id + e_{tij} \tag{12}
$$

$$
a_{0ij} = \beta_{00j} + \beta_{10j} Occup + u_{tj}, \tag{13}
$$

$$
a_{0ij} = \beta_{00j} + \beta_{10j} Occup + \beta_{20j} Exper + u_{tj}. \tag{14}
$$

The proportion of explained variance by each component is given by the increasing ratio of explained variance in the consecutively estimated models.

Appendix V: Expected likelihood of promotion

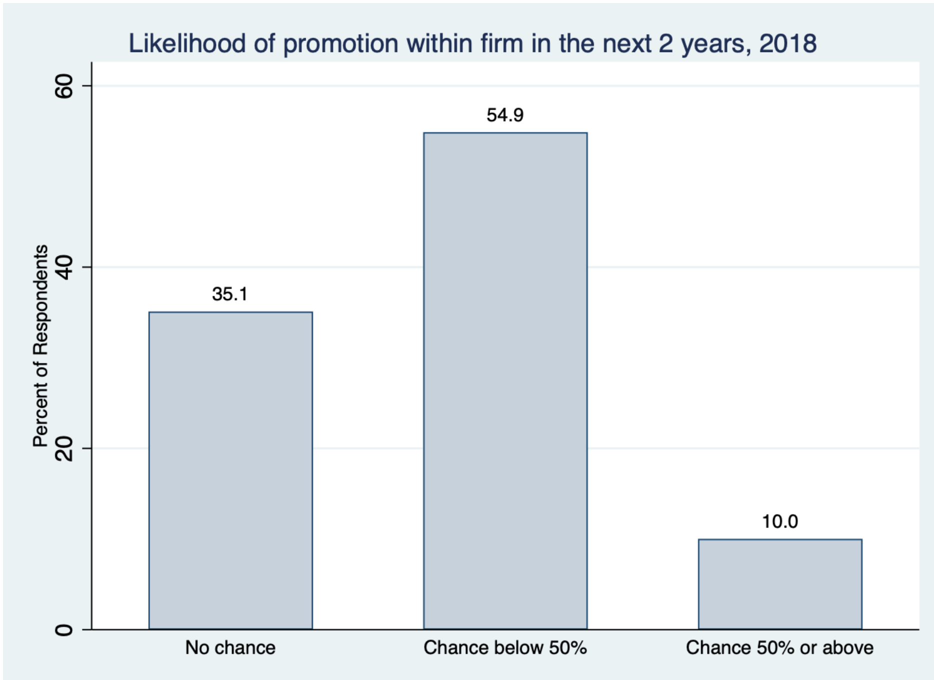


Figure SWA.3: Expected likelihood of promotion

The figure shows group sizes according to the reported expected likelihood to receive a promotion within one's establishment of employment in the following two years. SOEP survey wave 2018. All further sample restrictions as described in the main text apply.

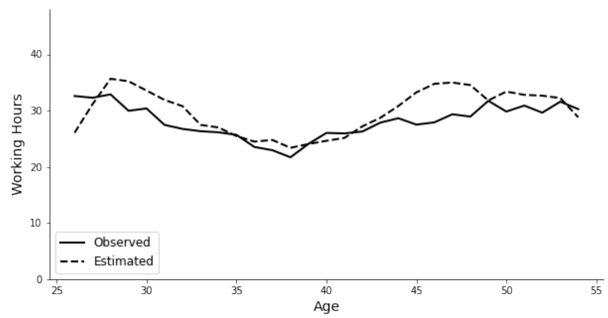
Appendix VI: Estimation details

To set starting values, I first estimate the parameters of the wave equations by GMM. In a second step I fit the model for the absorbing state of being in a senior position only. I start the joint estimation of all structural model parameters with the values estimated in these preliminary steps as starting values. Experience parameters of the wage equation enter the estimation procedure log-transformed.

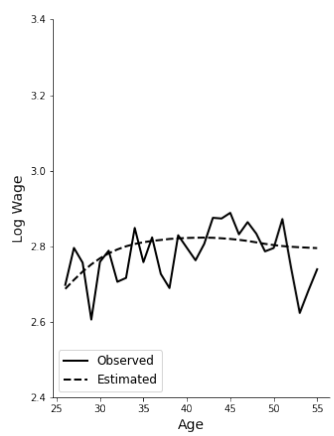
The estimation is performed using Py-BOBYQA, Cartis et al. (2019).

Appendix VII: Model fit

(a) **Working hours per week**



(b) **Log hourly wage, Level low**



(c) **Log hourly wage, Level high**

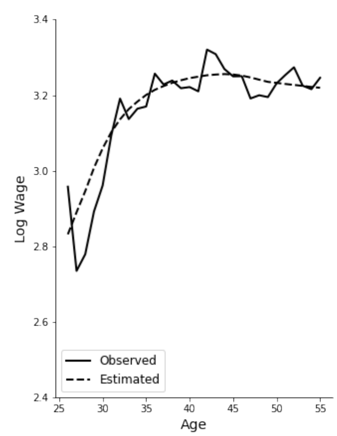


Figure SWA.4: Model fit

The figure shows how data simulated with the model and the estimated parameter vector match key patterns in the data. Panel (a) shows the fit between observed and simulated average weekly working hours by age, based on actual working hours reported in the SOEP estimation sample. This statistic is not directly targeted in the estimation process. Panels (b) and (c) show observed and simulated average age profiles of log wages at the low and high career levels, respectively.