Labor Supply Choices within Families

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Contents

List of Figures

List of Tables

1 Introduction

The awarding of the Nobel Prize to Claudia Goldin in 2023 underlines the importance of understanding women's labor-market outcomes. Claudia Goldin's extensive body of work has significantly advanced our knowledge about the development of female labor supply patterns, careers, and persistent gender wage gaps (e.g., Goldin 2006). Next to providing evidence on gender-based hiring practices (Goldin and Rouse 2000), her research has highlighted job flexibility that allows reconciling family and work (Goldin 2014) and the availability of contraceptives for family and career planning (Goldin and Katz 2002) as crucial factors that shape the evolution of women's labor market situation.

Central to Goldin's findings is the importance of the *family situation* for female labor supply and the gender wage gap. This thesis presents research that is part of the burgeoning literature on female labor supply and its relation to family dynamics, which particularly take into account women's dominant role in the provision of child care and home production.[1] Concerning family formation, child penalties on labor market participation, hours worked, and earnings after the birth of the first child have been documented for mothers but not for fathers (Angelov, Johansson, and Lindahl 2016; Kleven, Landais, and Søgaard 2019; Cortés and Pan 2023; Kleven, Landais, and Søgaard 2021; Andresen and Nix 2022). Regarding the conflicting demands of career and family that (high-skilled) women face, an increase in the supply of affordable substitutes for household production has been found to increase women's working hours in high-paying occupations with high rewards for overtime (Cortés and Tessada 2011; Cortés and Pan 2019). In addition, gender identity norms and the resulting gender roles within the family have been shown to influence choices with regard to women's labor supply and earnings (Bertrand, Kamenica, and Pan 2015; Bursztyn, Fujiwara, and Pallais 2017; Lippmann, Georgieff, and Senik 2020). Bertrand (2020) has pointed

[1] Olivetti and Petrongolo (2016) and Blau and Kahn (2017) provide in-depth reviews of the earlier literature, laying the groundwork for the more recent studies discussed below.

to gender differences in labor supply choices, especially after entering motherhood, as a main challenge on the path toward gender equality and stresses the importance of understanding the reasons for these different choices.

These insights pivot the focus toward the family as the critical unit of analysis in understanding labor-market dynamics, following the seminal work by Becker (1985). This thesis builds on Goldin's and Becker's foundation, exploring the labor-market situation of men and women from a family-economics perspective. It aims to examine the complex dynamics of decision-making within families and its consequential impact on labor-supply choices and career trajectories for both women and men.

My thesis is structured into three main chapters, each focusing on the role of the family for a specific dimension of labor supply that differs by gender. Specifically, it incorporates family-economics arguments into the analysis of gender gaps in wages, labor-market experience, and labor-supply elasticities. More precisely, the family dynamics considered are career prioritization, career interruptions, and the division of household chores. From a more general perspective, this thesis highlights the role of the family for the different choices of men and women regarding where to work, whether to work and how much to work. Thereby, this thesis contributes to the active field of research at the intersection of labor economics, family economics, and gender economics.

In Chapter 2 (joint work with Christian Bredemeier and Falko Jüßen) we propose a simple way to embed family-economics arguments for pay differences between genders into standard decomposition techniques of the wage gender gap.[2] The key common aspect of the family-based explanations for the wage gap is that important family decisions induce a trade-off between spouses' careers and that the family often has an incentive to prioritize the career of the spouse with the higher earnings potential. For the individual worker, this means that realized wages do not only depend on their own characteristics but also on whom they are married to. Two workers with identical characteristics but different partners are treated differently by their respective families and will thus experience different career trajectories.

[2] This chapter has been published in Averkamp, Bredemeier, and Juessen (2024). This thesis contains a slightly different and extended version of this article.

To account appropriately for the role of the family in the determination of wages, one has to compare men and women with similar own characteristics – and with similar partners. For the Oaxaca-Blinder decomposition approach, which remains the most frequently applied empirical decomposition approach of the gender wage gap, this means that the wage equation should include the characteristics of the individual's partner.

To make our point explicit, we set up a model of dual-earner couples deciding upon investments into spouses' careers. The model has two investment margins one of which includes a trade-off between spouses' careers (via joint location choice) and the other one allows for potential positive spill-over effects of investments into one partner's career on the career of the other partner. We use the model to show that a wage-gap decomposition that ignores partner characteristics misestimates the fraction of the wage gap that is due to observable characteristics, i.e., it misestimates the explained part of the wage gap. We then show that extending the decomposition by the characteristics of the partner resolves this problem and that our extended decompositions deliver unbiased results.[3]

We apply our improved decomposition to U.S. data from the Panel Study of Income Dynamics (PSID). We find that our extended decomposition explains considerably more of the wage gap than the standard approach – in line with our theory that highlights the role of career prioritization in dual-earner couples. Our empirical results single out work experience as a particularly important characteristic for explaining the wage gap. We corroborate that the neglect of the family situation is responsible for a substantial part of the supposedly unexplained wage gap by performing standard decompositions for *singles* and for married individuals without a working partner. In fact, we find that, for these groups, standard Oaxaca-Blinder decompositions attribute substantially larger shares of the gender wage gap to observable characteristics than they do for men and women living in dual-earner couples. Our results in this chapter stress the channel of career prioritization in the family, modeled as the decision where to work, and its connection to the observed gender gap in wages.

[3]Importantly, including partner characteristics does not mechanically increase the explained fraction of the gender gap. This only happens if the data are consistent with career prioritization or other mechanisms that induce one's own wage to depend *negatively* on the earnings potential of one's partner.

In Chapter 3, I focus on the decision whether to work and zoom in on accumulated career interruptions of women (measured in years of labor-market experience) by considering a particularly interesting case study: the striking regional differences between both women's accumulation of labor-market experience and the gender wage gap within Germany.

I analyze data from the German Socio-Economic Panel (SOEP) to investigate these patterns. In a preliminary analysis, I apply Oaxaca-Blinder decompositions to investigate the importance of labor-market experience for today's gender wage gap in Germany as well as for the gap in the gap between the country's Eastern and Western regions. For comparability to the literature, I use both, the standard Oaxaca-Blinder decomposition of the gender wage gap, and our extended decomposition proposed in Chapter 2 of this thesis. While the results underline that accumulated work experience contributes substantially to the gender wage gap in Germany, they also reveal that smaller experience gaps between men and women in the East contribute substantially to the wage gap being smaller there.

Given the importance of gender gaps in labor-market experience, I then investigate these differences more closely with a focus on how they differ between East and West Germany and why. I do so using a life-cycle regression approach with different measures of accumulated experience as dependent variable. In contrast to Chapters 2 and 4, the approach here is more explorative, using reduced-form regressions. Experience gaps between women in East and West Germany are mainly driven by mothers and their differing labor-supply decisions over the life cycle. Specifically, East German mothers spend significantly more years in the labor force. Interestingly, I find that the documented differences are hardly affected when controlling for worker and job characteristics, including education, marital status, industry, and occupation. This is different when I incorporate daycare supply into the analysis. First, I exploit regional differences in daycare supply for children below the age of three within East Germany. I show that East-West differences are substantially smaller when I control for a hypothetical experience measure that captures the East-West differences in daycare supply. Further, I show that East-West differences are constant in the number of children, which can be rationed with the different daycare entry ages in East and West Germany. This underscores the decisive role of child care in understanding the rather gender-egalitarian labor market of East Germany.

While the literature has further discussed East-West differences in social norms and attitudes toward maternal labor supply as likely explanations, I investigate another potential explanation in the German context which is again motivated by family-economics arguments. It could be that *men*, particularly fathers, in East Germany behave differently than in West Germany, thereby contributing to the higher labor-market participation of women in the East through informal childcare. There are no East-West differences in men's accumulated labor-force experience. Taken together, I interpret this set of results as corroborating the importance of external child care.

In Chapter 4 (joint work with Christian Bredemeier and Falko Jüßen), we focus on the role of the family for the decision on how much to work. Alesina, Ichino, and Karabarbounis (2011) have proposed a theoretical explanation, which is again a family-economics argument, for women's higher elasticities of market labor supply: the division of household chores between men and women. Alesina, Ichino, and Karabarbounis (2011) have worked out the optimal-tax implications of this elasticity pattern: women should be taxed at lower marginal rates ("gender-based taxation").

To investigate the roles of household specialization and preferences for labor-supply elasticities and the consequences for optimal taxation, we apply a model of joint decision making in dual-earner households regarding market labor supply and (unpaid) housework. We use our model for two purposes. Firstly, we derive labor-supply conditions that can be estimated empirically and identify two different concepts of labor-supply elasticities: the Frisch elasticity of market labor supply and the Frisch elasticity of total labor supply, respectively, the latter being the sum of market and housework hours. Anticipating that women on average spend more time in housework relative to their market hours compared to men, the model predicts that women's elasticity of market labor supply is larger than men's and that elasticities of total labor supply are both smaller than market elasticities and more similar across genders. Secondly, we use the model to determine the optimal relative marginal tax rates of the different members within a household. In line with the literature, we show that optimal relative marginal tax rates (inversely) reflect the relative elasticity of market labor supply and thus depend on exogenous preference parameters as well as the endogenous division of household chores.

In our empirical analysis, we use data from the Panel Study of Income Dynamics (PSID) to estimate the labor-supply conditions derived from our model. The results from these estimations serve to check the testable predictions of the model and as input into a subsequent quantitative optimal-taxation analysis. The results, firstly, confirm a significantly more elastic market labor supply of women. Secondly, they show that total hours respond less strongly to wage changes and in ways that are much more similar between genders. This speaks strongly in favor of the Alesina, Ichino, and Karabarbounis (2011) housework channel, while our results also point to some role of gender beyond the division of household chores.

Finally, we assess quantitatively to what extent implementable tax rules can mimic optimal relative tax rates within households. Both in our model as in the Alesina, Ichino, and Karabarbounis (2011) model, optimal relative tax rates depend on the division of household chores, which are difficult to observe and verify for the government. We quantify how good a proxy gender can be for optimal relative tax rates and compare this to alternative tax rules using observables which are also correlated to the division of household chores. Our results show that there are potential efficiency gains from gender-based taxation. Gender-based taxation is dominated, however, by income-based tax rules that tax married spouses individually rather than jointly.

Chapter 5 provides a summary. This work has shown that the family matters greatly for the decision whether to work, where to work, and how much to work, and it has provided methodological approaches that allow us to include the family in the theoretical and empirical analysis of labor-market outcomes for men and women. The results derived in this thesis provide insights that can be used for implementing policies that aim for higher female labor-market supply or equal pay.

2 Decomposing Gender Wage Gaps - A Family Economics Perspective

2.1 Introduction

The gender wage gap decreased substantially in the second half of the 20th century, but a persistent gap remains, see, e.g., Olivetti and Petrongolo (2016).[4] On average, women in the U.S. continue to earn close to 20% less per hour than men. As shown by, e.g., Blau and Kahn (2017), a considerable part of the wage gap can be related to observable gender differences in individual characteristics such as work experience, occupation, and industry. In turn, the closure of the gender wage gap can be explained to a substantial extent through women's catching up in terms of human capital, i.e., education and experience. However, an open question remains why the gender wage gap is (still) so large or, put differently, why a man with the characteristics of the average woman earns, according to the estimates of Blau and Kahn (2017), about 7 to 9 percent more than the average woman does.

There are two approaches in the literature that seek to explain remaining gender gaps. The first approach, reviewed by Bertrand (2011), Azmat and Petrongolo (2014), and Blau and Kahn (2017), argues that gender differences in personality traits or gender norms can lead to self-selection of women into lower-pay jobs and less steep career paths.[5] Several studies (Mueller and Plug 2006; Nyhus and Pons 2012; Le et al. 2011; Reuben, Sapienza, and Zingales 2024; Heinz, Normann, and Rau 2016; Chen, Grove,

[4]This chapter has been published in Averkamp, Bredemeier, and Juessen (2024). This thesis contains a slightly different and extended version of this article.

[5]There is a significant empirical literature, mostly experimental, on differences between men and women with respect to non-cognitive abilities, personality traits, and preferences, including the willingness to compete (Gneezy, Leonard, and List 2009; Flory, Leibbrandt, and List 2015; Buser and Yuan 2019), negotiation styles (Babcock and Laschever 2003; Exley, Niederle, and Vesterlund 2020), promotion-seeking (Bosquet, Combes, and García-Peñalosa 2019) the willingness to take on non-promotable tasks (Babcock et al. 2017), risk aversion (Croson and Gneezy 2009; Dohmen and Falk 2011), and self-promotion (Exley and Kessler 2022).

and Hussey 2017; Flinn, Todd, and Zhang 2018; Jung, Choe, and Oaxaca 2018; Roussille 2024) have documented that a part of the wage gap can be attributed to such factors, but their quantitative role seems to be limited.

The second approach emphasizes the role of the family as a catalyst for the gender wage gap. An important dimension is women's relative temporal inflexibility due to the dominant role in childcare and non-market work many families assign to women (e.g., Goldin 2014; Cortés and Pan 2023; Almås et al. 2023). At the same time, many husbands are their families' primary bread winners and see their careers prioritized in many decisions of the family such as family migration decisions (see, e.g., Mincer 1978; Compton and Pollak 2007; Foged 2016, and Braun, Nusbaum, and Rupert 2021), the choice of employers (see, e.g., Bredemeier 2019 and Petrongolo and Ronchi 2020), and job-search investments (Flabbi and Mabli 2018).

In this paper, we connect this family-based approach to the literature on decompositions of the gender wage gap. We propose a simple way to embed family-economics arguments for pay differences between genders into standard decomposition techniques. The key common aspect of the family-based explanations for the wage gap is that important family decisions induce a trade-off between spouses' careers and that the family often has an incentive to prioritize the career of the spouse with the higher earnings potential. For the individual worker, this means that realized wages do not only depend on their own characteristics but also on whom they are married to. Two workers with identical characteristics but different partners are treated differently by their respective families and will thus experience different career trajectories. For decompositions of the wage gap, whose purpose it is to compare *observationally identical men and women*, family economics implies that one should compare men and women with similar own characteristics *and similar partners* to account appropriately for the role of the family in the determination of wages.

For the Oaxaca-Blinder decomposition approach, which remains the most frequently applied empirical decomposition approach of the gender wage gap, this means that the wage equation should include the characteristics of the individual's partner. For example, on the right-hand side of the equation explaining a worker's wage, the workers's own education should be included but also the education of the worker's partner to account for the effect of the partner's education on the family's investment into the workers's career. In the decomposition, one would then capture the extent to which women's relative wages are compressed by their husbands' characteristics through career-prioritizing decisions of the family. The implication to include partner characteristics is not limited to the Oaxaca-Blinder approach but applies to all approaches that seek to assign a part of the wage gap to differences in observable characteristics. For example, matching-based approaches (e.g., Strittmatter and Wunsch 2021; Meara, Pastore, and Webster 2020) should include partner characteristics in the matching process, independent of the specifics of this process.

To make our point explicit, we set up a model of dual-earner couples deciding upon investments into spouses' careers. The model has two investment margins one of which includes a trade-off between spouses' careers and the other one allows for potential positive spill-over effects of investments into one partner's career on the career of the other partner. While there are many interpretations to the first channel, we frame it as a joint location choice where couples have to compromise between locations promoting the husband's career and locations promoting the wife's career. For a couple, it is rational to prioritize the career of the spouse with the higher earnings potential and it chooses to live closer to the place which promotes optimally the career of the spouse with the higher earnings potential. As a consequence, the realized wage of a worker depends positively on the individual's own earnings potential and – through the mediator distance to optimal location – negatively on the earnings potential of the individual's partner. The second investment choice, the spill-over channel, induces a positive relation between one's own wage and the partner's earnings potential as a high potential of the partner may induce the family to invest heavily into the partner's career, from which one's own career benefits as well.

We use the model to show that a wage-gap decomposition that ignores partner characteristics misestimates the fraction of the wage gap that is due to observable characteristics, i.e., it misestimates the explained part of the wage gap. Whether it overestimates or underestimates the explained gap depends on whether, on average, the career-prioritization or the spill-over effect is the dominant channel from partner characteristics to wages. With positive assortative mating along observables, the explained wage gap is underestimated when the career-prioritization channel is dominant. Reversely, the spill-over channel being dominant would imply that the standard decomposition overstates the explained wage gap. We then show that extending the decomposition by the characteristics of the partner resolves this problem and that our extended decompositions deliver unbiased results.[6]

We apply our improved decomposition to U.S. data from the Panel Study of Income Dynamics (PSID). In line with the literature, we document that standard Oaxaca-Blinder decompositions explain roughly half of the gap and hence suggest that a substantial part of the wage gap is unrelated to the included characteristics such as human-capital variables and job information. Our extended decompositions systematically explain larger shares of the wage gap as a consequence of gender differences in observable characteristics. This suggests that partner characteristics are an important determinant of workers' wages and that, in general, workers tend to earn lower wages when they are married to partners with high earnings potentials. This supports the notion of career prioritization in line with many papers from the family-economics literature. We also find that, for some characteristics that are important for explaining wages in the cross-section but that are of lesser importance for explaining wage gaps, such as education, the spill-over channel is the dominant one. Our results imply that, on average, men's wages are fostered by up to 10% through family decisions that favor their careers relative to a counterfactual without incentives for career prioritization. This translates into a substantial reduction in the unexplained gender wage gap when partner characteristics are included. For some years, the extended decomposition explains up to 100% of the gap.

We corroborate our results in an extensive sensitivity analysis, in which we vary sample selection criteria, the wage covariates included in the decomposition, functional form assumptions, and where we estimate spouses' wage equations jointly. An important challenge when measuring and decomposing gender gaps on the labor market is women's selection into the labor force, which may depend also on their partners'

[6] Importantly, including partner characteristics does not mechanically increase the explained fraction of the gender gap. This only happens if the data are consistent with career prioritization or other mechanisms that induce one's own wage to depend *negatively* on the earnings potential of one's partner. To clarify, our point goes beyond simply arguing that *additional* characteristics should be included in the Oaxaca-Blinder approach, but instead relates to the way *how* characteristics that have been isolated as important by the literature should enter the decomposition. Suppose, for example, the wage gap were entirely due to differences in work experience. Then, a standard Oaxaca-Blinder decomposition with years of experience would still label some part of the gap as "unexplained" because differences in experience affect the wage gap twice – through the direct effect of experience on earnings potentials and through career prioritization in favor of the more experienced partner. The standard approach captures only one of these channels.

characteristics. It is an advantage of standard decomposition techniques including our extended decomposition to quantify how large a wage gap can be explained through differences in characteristics with only estimating a wage equation for men, for which selection is less an issue, and use it to determine a counterfactual wage prediction for women. When we do so for a broad (and hence less selective) sample of women in couple households, rather than a narrower sample of dual-earner households, we confirm that a larger part of the wage gap can be explained when husbands' characteristics are included compared to a standard approach.

Our empirical results single out work experience as a particularly important characteristic for explaining the wage gap. As is known in the literature, experience is valued by employers, and men and women differ substantially in this characteristic – mostly due to women often having to interrupt their (full-time) careers after child births. We find that this widens the gender wage gap beyond the direct effect of women's foregone accumulation of experience on their wages. It appears that families prioritize husbands' careers when wives' careers prospects are dampened by their lack of experience. We corroborate the effect of wives' lack of experience on husbands' wages through using predicted experience based on age, education, and numbers of children, thereby eliminating the risk of reverse causality (from men's wages to women's career interruptions).

We corroborate that the neglect of the family situation is responsible for a substantial part of the supposedly unexplained wage gap by performing standard decompositions for *singles* and for married individuals without a working partner. For these groups, career prioritization or related aspects specific to dual-earner households do not play a role. In fact, we find that, for these groups, standard Oaxaca-Blinder decompositions attribute substantially larger shares of the gender wage gap to observable characteristics than they do for men and women living in dual-earner couples.

Overall, our results imply that pay differences between men and women are more strongly related to differences in observable characteristics than suggested by standard decompositions, stressing the role of family decisions for the observed pay gap. To be clear, our results do not rule out discrimination against women. Our empirical results indicate that, in most years, the labor market does not yield the same wages for men and women even conditional on their, and their partners', observable characteristics. Important determinants of earnings potentials such as career interruptions or occupation choices are plausibly affected by gender roles, stereotypes, or prejudices.[7] Moreover, career prioritization amplifies both non-discriminatory and discriminatory differences in earnings potentials. A family observing that women are discriminated against faces incentives to prioritize the husband's career over the wife's even if the two are identical in terms of objective characteristics. Policy might exploit the amplification mechanism of career prioritization as policy measures that improve women's earnings potentials can result in families investing more strongly in women's careers, thereby reinforcing the direct effects on the wage gap.

The remainder of this paper is organized as follows. We review additional related literature in Section 2.2. In Section 2.3, we present the model and use it to study alternative decomposition approaches in Section 2.4. In Section 2.5, we present our empirical analysis. Section 2.6 concludes.

2.2 Related literature

Our paper is particularly related to two papers that emphasize the role of the family for explaining gender gaps. First, Cortés and Pan (2023) show that a large part of the unexplained gender earnings gap in the U.S. can be assigned to the unequal effect of children on the careers of mothers and fathers. They rationalize this finding in a model where parents decide upon who reduces working time (and accepts an earnings penalty) based on their relative earnings potentials. The spouse with the lower potential is selected to reduce hours and earnings differences between spouses thus widen. Our paper provides additional evidence about the *mechanisms* from children to wage gaps, which run through experience but go beyond a simple foregone-experience argument.

Second, Almås et al. (2023) show that women tend to marry husbands who have higher earnings potentials than themselves, with top-potential women remaining without partner disproportionately often. Almås et al. (2023) argue that the resulting within-couple differences in earnings potentials lead to household decisions favoring men's careers which can explain the occurrence of gender gaps even without systematic differences between men and women in the overall population. Their argument is similar to ours

[7] For example, empirical evidence shows that female labor supply and hence the accumulation of work experience is affected by gender identity norms (Bertrand, Kamenica, and Pan 2015) and cultural factors (Blau et al. 2020).

as it points to a channel which leads to women not realizing their earnings potentials because of decisions of their family which respond to intra-household relative potentials. Their argument and ours complement each other as they point to a reason for gender gaps in wages without gaps in potentials while we propose a channel that amplifies the effect of relative potentials on relative wages. Taken together, the two papers imply that gender gaps in wages remain considerable even though gender gaps in wage-relevant characteristics are small because there would be gender gaps in wages even without any gender differences in relevant characteristics (the Almås et al. argument) and because relatively small differences in characteristics can induce relatively large gaps in wages (our argument).

While our theory remains agnostic about the specific mechanism through which wages are influenced by partner characteristics (our model summarizes all relevant dimensions of family life where trade-offs occur between spouses' working lives in a one-dimensional variable which we interpret as "location" for simplicity), the literature has discussed several additional mechanisms that have similar implications as the one highlighted in our model:

Cortés and Tessada (2011) and Cortés and Pan (2019) emphasize temporal inflexibility of secondary earners associated with their family obligations. In occupations where wages are highest, individuals have to work long hours to have a successful career. For the family, the cost of supplying long working hours is convex, i.e., working long hours is more costly if one's partner is already working long hours, for example due to child-care obligations. Then, the optimal time allocation mostly promotes the designated primary earner's career while designated secondary earners may forego important investments into their careers. Cortés and Tessada (2011) show that a decrease in the costs of services that are close substitutes to household production increases the labor supply of highly skilled women. The effect is strongest in occupations where success is related to working longer hours. This suggests that women's careers came second to their husbands' ones before the cost reduction. Hence, restrictions on affordable household help and the resulting optimal time allocation between spouses reveal the link between wages and an individual's role in the family.

Bredemeier (2019) shows that wages are affected by earner roles in the household through the choice of which employer to work for. In his model, there is a trade-off between pay and non-pay attributes of jobs and high earnings of the partner reduce the importance of the pay dimension in one's own employer choice. As a result, designated secondary earners weigh non-pay job attributes rather strongly when choosing employers and the wage sensitivity of an individual's job choice depends positively on the share that the individual contributes to household income. Firms with monopsonistic power on the labor market exploit this and pay lower wages to individuals married to partners with high earnings potentials. Relatedly, Petrongolo and Ronchi (2020) provide evidence that women more often than men trade off better earnings for non-pay job attributes such as shorter commutes or flexible work schedules. Albrecht et al. (2018) document that men experience higher wage gains upon switching employers than women, whose firm-to-firm transitions appear motivated by job attributes other than pay. Arguably, the importance of these attributes reflects women's role as the primary child-care provider in most households – which can be expected to be more pronounced the higher is the husband's earnings potential relative to the wife's one.

Hotz, Johansson, and Karimi (2018) show that women switch to more "family-friendly" jobs upon motherhood. Pertold-Gebicka, Pertold, and Datta Gupta (2016) show that women around motherhood switch from sector jobs with time pressure and returns to long hours to private sector jobs after the birth of a child, and that these transitions are related to pre-birth occupational characteristics such as time pressure and the convexity of pay (i.e. earnings returns to working long hours). Mas and Pallais (2017) document that women, in particular those with young children, have a higher willingness to pay for family-friendly job attitudes.

Adda, Dustmann, and Stevens (2017) show that women take such decisions already in response to intended fertility and not only when children are already born. Wasserman (2023) shows that women enter more family-friendly jobs already early in their career, presumably in anticipation of future family and child-care obligations. Wiswall and Zafar (2018) show that women have a higher willingness to pay for family-friendly job attitudes already among college students, almost all of which do not yet have children of their own.

Foged (2016) provides a model of the joint location choice of dual-earner households but focuses on the extensive-margin choice *whether* to move to another location rather than the intensive-margin choice *where* to locate, which is the focus of our paper. Also in Foged (2016), wages depend on location and it is rational for a household to decide on a location that promotes the designated primary earner's career. This tends to have negative consequences for wage rates paid to the secondary earner, as in our model. In line with primary earners' careers being prioritized in family migration decisions, Mincer (1978) documents that, when families migrate, wives' employment rates fall and husbands' wages rise. Compton and Pollak (2007) document that primarily husbands' education explains the propensity of couples to migrate to large metropolitan areas. Braun, Nusbaum, and Rupert (2021) shows that families migrate more often when they have a clear primary earner.

Another dimension where family decisions affect both husband's and wife's career is their joint job search. Flabbi and Mabli (2018) show that the gender gap in accepted wages can exceed the gap in wage offers considerably because couple households may accept low job offers for women in order to be able to afford searching for high-wage jobs for men. A counteracting effect of joint search behavior of couples is discussed by Pilossoph and Wee (2021) who argue that marital wage premia can increase in spousal education because the latter elevates reservation wages through an increased willingness to bear risk.

2.3 A model of career investments in dual-earner households

The model has two stages, a marriage-market stage and a career-investment and consumption stage. We solve the model by backward induction, starting with the career-investment and consumption stage in Section 2.3.1. There we take as given the distribution of individual characteristics in marriages. We characterize this distribution in the marriage market equilibrium in Section 2.3.2.

2.3.1 Career-investment and consumption stage

The notation of the household structure in the model is as follows: individual i lives in household I and his or her spouse is indexed by $-i$. The matching of individuals into couples is determined in the marriage market stage that is discussed in Section 2.3.2. We consider couple households that have to decide over two forms of career investments. Regarding one choice, there is a potential conflict between spouses' careers. For simplicity, we call this choice "location" but other interpretations, such as the allocation of housework and family responsibilities, would have similar implications. Location is a continuous variable $r \in (0, 1)$. An individual's ideal location, i.e., the location where (s)he can earn the highest wage is denoted by a_i. The second choice does not include a conflict but concerns how many resources y to invest in order to promote both members' careers. Our interpretation of r comprises everything where a household might have to compromise between its members' careers. The difference $|a - r|$ measures how much life in the family differs from the way it would be best for the individual's career and can for example be understood as the reduction in the set of possible jobs and the loss of working-time flexibility associated with child-care obligations. On the other hand, y should be understood as choices which are mutually beneficial to both members' careers such as the formation of a network both members can benefit from. Alternatively, one might understand y as how much the household is willing to invest into its members' careers and r as how strongly this investment is targeted toward one partner in particular. As discussed in more detail later, with these two choices, our model features a channel that we will call "career-prioritization channel" (through which wages can depend *negatively* on partner characteristics) as well as a "spill-over channel" (through which wages can depend *positively* on partner characteristics).

The wage W_i of individual i in location r with investment y consist of three elements,

$$W_i = \psi_i z_{i,r} y_I, \tag{2.1}$$

where ψ_i denotes the earnings potential of individual i, reflecting individual characteristics such as education and experience (see below), $z_{i,r}$ is a location-worker match variable, and factor y reflects the effects of mutual beneficial career investment.

We assume that the location-worker match variable is given by

$$z_{i,r} = 1 - (r - a_i)^2. \tag{2.2}$$

If the individual is in a location that differs from her ideal one, there is a wage penalty captured by $(r - a_i)^2$. The strength of this penalty depends on the distance between the actual location and the ideal one.

Couple I receives utility $u(c_{I,r})$ from household consumption $c_{I,r}$, with derivatives $u' > 0$ and $u'' < 0$. The couple's budget constraint at location r is given by

$$c_{I,r} = W_i + W_{-i} - \frac{1}{\eta} y_I^2. \tag{2.3}$$

The parameter η measures the productivity, or inverse cost, of the career investment y. It will determine how much resources couples invest into their careers and thereby the importance of the spill-over channel. The couple's decision problem is to maximize $u(c_{I,r})$ subject to (2.1), (2.2), and (2.3) by choosing the optimal location for the couple household and the optimal level of mutually beneficial investments, which by substituting in the constraints reads

$$\max_{r,y} \; u\left(\psi_i \left(1 - (r - a_i)^2\right) y + \psi_{-i} \left(1 - (r - a_{-i})^2\right) y - \frac{1}{\eta} y^2\right).$$

The optimal choices for location and the mutually beneficial investment are given by

$$r_I^* = \frac{\psi_i}{\psi_i + \psi_{-i}} a_i + \frac{\psi_{-i}}{\psi_i + \psi_{-i}} a_{-i} \tag{2.4}$$

and

$$y_I^* = \frac{\eta}{2} \left(\psi_i + \psi_{-i} - \frac{\psi_i \psi_{-i}}{(\psi_{-i} + \psi_i)^2} (a_i - a_{-i})^2\right). \tag{2.5}$$

Equation (2.4) illustrates that the household chooses its location as a weighted average of the ideal locations of its members. The weights are given by the relative earnings potentials of the two partners. The higher the earnings potential of either member, the closer the household moves to this member's ideal location. Through this channel, the household prioritizes the career of the spouse with the higher earnings potential. Equation (2.5) in turn shows that there are economies of scale in the mutually beneficial career investment. Investment increases in both members' earnings potential. Even though the household might decide for the investment primarily to foster the career of the spouse with the higher earnings potential, the returns spill over into the career of the other spouse as well. The two choices have counteracting implications regarding the impact of the partner's earnings potential on one's own wage. Through location choice, a higher earnings potential of the partner tends to reduce an individual's wage as the household puts more weight on the partner's career. Through y, on the other hand, an individuals' wage tends to be fostered through a high earnings potential of the partner as investment is more attractive, from which both wages benefit.

Now consider log wage rates, $w_i = \log W_i$,

$$w_i = \log \psi_i + \log z_{i,r} + \log y_I,$$

and substitute in the optimal choices (2.4) and (2.5) to obtain equilibrium log wages w_i:

$$\begin{aligned} w_i =& \log \psi_i + \log \left(1 - \left(\frac{\psi_{-i}}{\psi_i + \psi_{-i}} (a_{-i} - a_i) \right)^2 \right) \\ &+ \log \frac{\eta}{2} \left(\psi_i + \psi_{-i} - \frac{\psi_i \psi_{-i}}{(\psi_i + \psi_{-i})^2} (a_i - a_{-i})^2 \right). \end{aligned} \tag{2.6}$$

The second term can be interpreted as the penalty resulting from not living at one's ideal location. The third term is the result of the mutually beneficial career investment.

This simple model of career investments implies that, for any given difference in ideal locations a_i and a_{-i} (which an econometrician cannot observe), individuals' wages depend on both, their own as well as their partners' characteristics, ψ_i and ψ_{-i}. In which direction the partner's earnings potential ψ_{-i} affects the (log) wage rate w_i, depends on the relative strengths of the career-prioritization and spill-over channels.

2.3.2 Marriage-market stage

To characterize the distribution of individual characteristics within marriages, both observable to the econometrician and unobservable, we now endogenize the formation of couple households on the marriage market. We abstract from non-economic determinants of match quality such as love and, for simplicity, assume a frictionless marriage market.

Once married, spouses consume a household-public consumption basket over which they have homogeneous preferences, i.e., in any marriage, the wife's utility equals the husband's utility. Given their subsequent optimal investment choices, the marriage market is characterized by non-transferable utility matching.

We denote men by $m \in M$ where M is the set of all men. Likewise, women are denoted by $f \in F$ where F is the set of all women. Their respective utilities as a function of whom they marry we denote by $v_m(f,m)$ for women's utility and $v_f(f,m)$ for men's. In our model, $v_m(f,m) = v_f(f,m)$.

For the marriage market to be in equilibrium, no two individuals may have incentives to break from their current marriages to form a new marriage together in which they were better off. Formally, the equilibrium requirement is that there are no two individuals f' and m^* married to m' and f^*, respectively, for whom

$$v_f\left(f', m^*\right) \geq v_f\left(f', m'\right)$$

while, at the same time,

$$v_m\left(f', m^*\right) \geq v_m\left(f^*, m^*\right).$$

If this requirement is fulfilled, the marriage-market equilibrium is characterized by

$$v_f(i) = \max_{z \in M}\left(v_f(i,z) \,|\, v_m(i,z) \geq v_m(z)\right) \tag{2.7}$$

and

$$v_m(i) = \max_{z \in F}\left(v_m(z,i) \,|\, v_f(z,i) \geq v_f(i)\right). \tag{2.8}$$

Using the results from Section 2.3.1, we obtain

$$\begin{aligned} v_f(i) = v_m(-i) = u\Bigg(\exp\Bigg(\sum_{j=i,-i} \log\psi_j + \log\left(1 - \left(\frac{\psi_j}{\psi_j + \psi_{-j}}\left(a_j - a_{-j}\right)\right)^2\right) \\ + \log\frac{\eta}{2}\left(\psi_m + \psi_f - \frac{\psi_g\psi_{-g}}{\left(\psi_j + \psi_{-j}\right)^2}\left(a_j - a_{-j}\right)^2\right)\Bigg)\Bigg). \end{aligned}$$

That is, the marriage market tends to bring together spouses with similar earnings potentials and similar optimal locations. Yet, if earnings potentials and optimal locations are not perfectly correlated, perfect assortative mating is not possible along both dimensions simultaneously. Hence, some agents marry partners whose optimal locations differ from their own ones but who have earnings potentials that stabilize the respective marriage. This process will in general lead to non-trivial joint distributions of earnings potentials and ideal locations in marriages.[8]

[8] Appendix 2.A illustrates a two-couple example.

While individual ideal locations a_i and their distribution $f(a)$ with mean μ and variance σ^2 are given exogenously, the correlation between the ideal locations of partners, denoted by κ, results endogenously on the marriage market and depends on the joint distribution of ideal locations a and earnings potentials ψ across individuals. As a consequence, there will in general result a non-perfect correlation between partners' ideal locations in a marriage, i.e., $\kappa < 1$. This is important because the career-prioritization channel would become irrelevant if every individual married a partner with an identical ideal location. Accounting for love shocks or matching frictions would introduce further random elements into the marriage market, moving the equilibrium even further away from this trivial extreme case.

2.3.3 Linking equilibrium wages to characteristics

To perform an Oaxaca-Blinder wage-gap decomposition in the model, we need to link earnings potentials ψ to observable characteristics of the workers and linearize the wage equation. We express earnings potentials as a function of individual characteristics Z_i,

$$\log \psi_i = \gamma_{g(i)} Z_i,$$

where $g(i)$ denotes individual i's gender and can take the values m (for male) and f (for female). Z_i is a column vector of individual characteristics of individual i and $\gamma_{g(i)}$ is a row vector of parameters. In general, the mapping from characteristics to earnings potentials can be gender-specific (such that $\gamma_m \neq \gamma_f$) which allows us to capture discrimination.

To obtain a log-linear relation between wages and characteristics, we apply a first-order Taylor approximation of the equilibrium wage equation (2.6) around a symmetric situation with $\psi_i = \psi_{-i} = \psi$, where ψ is the mean earnings potential in the economy, which we normalize to one, and values for a_i and a_{-i}, respectively, that lead to the penalty term $(a_{-i} - a_i)^2$ in the wage equation (2.6) taking its expected value $2(1-\kappa)\sigma^2$.[9] This point of approximation ensures that both, the earnings potential ψ, which reflects individual characteristics, and the log wage w take their average values. It can thus be understood as the centroid of a regression of log wages on the individual characteristics

[9] The expected value of $(a_{-i} - a_i)^2$ is $\mathrm{E}(a_i - a_{-i})^2 = \mathrm{E}\left(a_i^2 - 2a_i a_{-i} + a_{-i}^2\right) = 2\,\mathrm{E}\left(a_i^2\right) - 2\,\mathrm{E}(a_i a_{-i}) = 2\left(\mathrm{E}\left(a^2\right) - \mathrm{E}(a)^2 - \mathrm{cov}(a_i, a_{-i})\right) = 2(\mathrm{var}(a) - \mathrm{cov}(a_i, a_{-i})) = 2(\sigma^2 - \kappa\sigma^2) = 2(1-\kappa)\sigma^2$.

embodied in the earnings potential ψ. We choose this point of approximation rather than gender-specific average earnings potentials in order to approximate the model around a situation where the family treats both spouses' careers evenly.[10]

Applying the approximation gives

$$w_i \approx \beta_0 + \beta_{1,g(i)} Z_i + \beta_{2,g(i)} Z_{-i} + \varepsilon_i, \tag{2.9}$$

where

$$\begin{aligned}
\beta_0 &= \log\left(1 - \frac{1}{2}\phi^2\right) - \left(\frac{2\phi}{2-\phi^2} - \frac{\eta}{2}\sqrt{(1-\kappa)\sigma}\right)\sqrt{(1-\kappa)\sigma} \\
\beta_{1,g(i)} &= \left(\frac{\phi^2}{2-\phi^2} + \frac{\eta}{2}\right)\gamma_{g(i)} \\
\beta_{2,g(i)} &= -\left(\frac{\phi^2}{2-\phi^2} - \frac{\eta}{2}\right)\gamma_{g(-i)}
\end{aligned}$$

and

$$\varepsilon_i = \left(\frac{\sqrt{2}\phi}{2-\phi^2} - \frac{\eta}{2}\sqrt{\frac{(1-\kappa)}{2}\sigma}\right)(a_i - a_{-i}).$$

Appendix 2.B provides a a derivation. Condition (2.9) can be read as a regression equation. In a regression of the log wage on the worker's own characteristics and the partner's characteristics, β_0 is a constant, $\beta_{1,g(i)}$ and $\beta_{2,g(i)}$ are vectors of coefficients, and ε_i is a (mean-zero) residual since ideal locations a_i and a_{-i} cannot be observed by the econometrician. Note that the entries in $\beta_{1,g}$ tend to have the opposite sign compared to their counterparts in $\beta_{2,g}$ when the career-prioritization channel is dominant (small η) and the same sign when the spill-over channel is dominant (large η).

2.4 Wage-gap decompositions in the model

In the model, gender differences in pay can stem from differences in the characteristics Z and from differences in how earnings potentials depend on characteristics as captured by the coefficients γ and, consequently, β. In order to separate these two sources, the

[10]Note that wages are convex in both one's own and one's partner's earnings potential. Approximation errors thus go in the same direction for both men and women.

(average) gender wage gap $\Delta = \overline{w}_m - \overline{w}_f$, where $\overline{w}_g$ denotes average log wages by gender, can be decomposed as

$$\Delta = \underbrace{(\beta_{1,m} - \beta_{2,m}) \cdot (\overline{Z}_m - \overline{Z}_f)}_{\Delta|_Z} + \underbrace{(\beta_{1,m} - \beta_{1,f}) \cdot \overline{Z}_f + (\beta_{2,m} - \beta_{2,f}) \cdot \overline{Z}_m}_{\Delta|_\beta}, \qquad (2.10)$$

where $\overline{Z}_g$ denotes gender-specific average characteristics. The first term on the right-hand side, $\Delta|_Z$, is the wage gap that is due to gender differences in characteristics Z. It comprises both the effect that these characteristics exert on one's own wage and the one that they exert on one's partner's wage. The second term, $\Delta|_\beta$, is the wage gap that is due to gender-specific coefficients, including intercepts – it is zero when the coefficients are the same for both genders.

2.4.1 Career investment and empirical wage-gap decompositions

We now analyze *empirical* decomposition approaches to the gender wage gap in our model of career prioritization. We will show that the standard Oaxaca-Blinder approach, in which a worker's wage is related only to the worker's own characteristics, misstates the share of the wage gap due to observable characteristics. We will then show that an extended decomposition where the characteristics of the worker's partner are included in the wage equation solves this problem.

Standard Oaxaca-Blinder decomposition. The first step of the standard Oaxaca-Blinder decomposition is to estimate a log wage equation for one gender, typically for men:

$$w_i = b_{0,g(i)} + b_{1,g(i)} \cdot X_i + e_i, \qquad (2.11)$$

where index g denotes gender, $b_{0,g(i)}$ is a constant, $b_{1,g(i)}$ is a vector of coefficients, X_i is a vector of observable characteristics, and e_i is a residual.

The empirical decomposition yields an "explained" part of the gap,

$$\left(\widehat{\Delta}|_X\right)^{std} = \widehat{b}_{1,m}^{std}(\overline{X}_m - \overline{X}_f),$$

where $\widehat{b}^{std}$ indicates estimates, that is assigned to differences in observable characteristics and an "unexplained" part

$$\left(\widehat{\Delta}|_b\right)^{std} = \widehat{b}^{std}_{0,m} - \widehat{b}^{std}_{0,f} + (\widehat{b}^{std}_{1,m} - \widehat{b}^{std}_{1,f})\overline{X}_f \tag{2.12}$$

that this approach identifies as unrelated to observable characteristics.

Extended decomposition. We propose an extended decomposition that accounts for the role of the family for individual wage rates in dual-earner households. Specifically, we account for the characteristics of the individual's partner and estimate

$$w_i = b_{0,g(i)} + b_{1,g(i)} \cdot X_i + b_{2,g(i)} \cdot X_{-i} + e_i, \tag{2.13}$$

which yields an explained gap of

$$\left(\widehat{\Delta}|_X\right)^{ext} = \widehat{b}^{ext}_{1,m}(\overline{X}_m - \overline{X}_f) + \widehat{b}^{ext}_{2,m}(\overline{X}_f - \overline{X}_m) = \left(\widehat{b}^{ext}_{1,m} - \widehat{b}^{ext}_{2,m}\right)(\overline{X}_m - \overline{X}_f)$$

and an unexplained gap of

$$\left(\widehat{\Delta}|_b\right)^{ext} = \widehat{b}^{ext}_{0,m} - \widehat{b}^{ext}_{0,f} + (\widehat{b}^{ext}_{1,m} - \widehat{b}^{ext}_{1,f})\overline{X}_f + (\widehat{b}^{ext}_{2,m} - \widehat{b}^{ext}_{2,f})\overline{X}_m. \tag{2.14}$$

If the set of observable characteristics X in the decomposition includes all characteristics Z relevant for earnings potentials ψ, the extended decomposition identifies correctly the shares of the gender wage gap which are due to differences in these characteristics and due to differences in coefficients ($\Delta|_Z$ and $\Delta|_\beta$), respectively. This is not surprising since the wage equation in the extended decomposition (2.13) is identical to the data-generating wage equation (2.9). By contrast, the standard decomposition misestimates the importance of differences in characteristics *even if the wage equation accounts for all variables Z which are relevant for earnings potentials and wages* because it fails to account for the career-prioritization and spill-over channels through which these variables impact on gender-specific wages. We will now demonstrate this point.

2.4.2 Comparing the decompositions

For simplicity, we restrict the set of characteristics in Z to a single observable characteristic, x. We consider the case where both decomposition approaches account for this characteristic, albeit in different ways. For simplicity, we assume that the characteristic is measured in a way that it increases earnings potentials, $\gamma_{x,g} > 0$ (a classic example is human capital) and that some part of the gender wage gap can in fact be attributed to this characteristic, i.e., $\overline{x}_m > \overline{x}_f$.

The *standard Oaxaca-Blinder wage regression* yields a coefficient on male workers' characteristic of

$$\widehat{b}_{1,m}^{std} = \beta_{1,m} + \beta_{2,m} \cdot \frac{\operatorname{cov}(x_m, x_f)}{\operatorname{var}(x_m)}$$

due to the omitted-variable bias related to the partner characteristics x_{-i}. Thus, the standard Oaxaca-Blinder decomposition yields an explained gender wage gap of

$$\widehat{\Delta}|_x = \widehat{b}_{1,m}^{std} \cdot (\overline{x}_m - \overline{x}_f) = \left(\beta_{1,m} + \beta_{2,m} \cdot \frac{\operatorname{cov}(x_m, x_f)}{\operatorname{var}(x_m)}\right) \cdot (\overline{x}_m - \overline{x}_f).$$

As a comparison, the gap which is truly due to differences in the characteristic x is

$$\Delta|_x = (\beta_{1,m} - \beta_{2,m}) \cdot (\overline{x}_m - \overline{x}_f),$$

see (2.10) for $X = x$. Hence, the estimated explained gap differs from the true explained gap,

$$\widehat{\Delta}|_x \neq \Delta|_x,$$

as long as $\operatorname{cov}(x_m, x_f) / \operatorname{var}(x_m) > -1$, i.e., as long there is not perfectly negative assortative mating along characteristics.

Whether the standard decomposition overestimates or underestimates the explained gap depends on whether the career-prioritization or the spill-over effect is the dominant channel from partner characteristics to wages. Assuming that there is positive assortative mating, $\operatorname{cov}(x_m, x_f) > 0$, the standard decomposition understates the explained wage gap, $\widehat{\Delta}|_x < \Delta|_x$, when the career-prioritization channel is dominant, i.e., if $\beta_{2,m} < 0$. Reversely, the spill-over channel being dominant would imply that the standard decomposition overstates the explained wage gap.[11]

By contrast, estimating the *extended wage equation for the decomposition* gives the coefficients $\widehat{b}_{1,m}^{ext} = \beta_{1,m}$, and $\widehat{b}_{2,m}^{ext} = \beta_{2,m}$. Thus, the estimated explained gap is

$$\widehat{\Delta}|_x = \widehat{b}_{1,m}^{ext}(\overline{x}_m - \overline{x}_f) + \widehat{b}_{2,m}^{ext}(\overline{x}_f - \overline{x}_m) = (\beta_{1,m} - \beta_{2,m})\,(\overline{x}_m - \overline{x}_f)$$

and corresponds to the true explained gap $\Delta|_x$, see (2.10). The estimated unexplained gap is $\widehat{\Delta}|_b = \Delta - \widehat{\Delta}|_x = (\beta_{1,m} - \beta_{1,f}) \cdot \overline{x}_f + (\beta_{2,m} - \beta_{2,f}) \cdot \overline{x}_m$ and equals the true unexplained gap $\Delta|_\beta$.

The main implication of our analysis is that we should expect the explained gender wage gap to change when we extend an Oaxaca-Blinder decomposition by partner characteristics. Yet, including these additional (partner) characteristics does not mechanically increase the explained fraction of the gender gap. This only happens if the data are consistent with career prioritization being the dominant channel through which partners' earnings potentials affect wages (i.e., $\beta_{2,m} < 0$).

2.5 Empirical analysis

In this section, we apply our extended Oaxaca-Blinder decomposition empirically using data from the Panel Study of Income Dynamics (PSID). The PSID is the most suited U.S. data set for decompositions of the gender wage gap as it has information on actual labor market experience, a key explanatory variable for the gender wage gap.[12] For comparability to the literature, we follow Blau and Kahn (2017) in terms of sample selection, and in the choice and definition of explanatory variables. As Blau and Kahn (2017), we use data for the years 1980, 1989, 1998, and 2010.[13]

[11]Under negative assortative mating, the standard decomposition overstates (understates) the explained gap if the career-prioritization (spill-over) channel is dominant. Yet, negative assortative mating is at odds with empirical evidence.

[12]The PSID is widely used for studying women's wages and labor supply, see, e.g., Altug and Miller (1998), Olivetti (2006), Albanesi and Olivetti (2009), Gayle and Golan (2012), Blau and Kahn (2017) and Cortés and Pan (2023).

[13]Earnings in the PSID refer to the previous year. Hence, we use, e.g., the 1981 data to measure wages in 1980.

2.5.1 Sample selection, explanatory variables, and descriptive statistics

Sample. We start with a sample of full-time workers. Following Blau and Kahn (2017), we select employees between ages 25 and 64 working full-time in the non-farm/non-military sector for at least 26 weeks per year, excluding the self-employed as well as the immigrant and Latino samples.[14] We then select different subsamples of full-time workers, most importantly the subsample of workers living in dual-earner households.[15]

To construct a sample of workers living in dual-earner households, which is necessary for our extended Oaxaca-Blinder decomposition, we restrict the sample of full-time workers to married or cohabiting individuals with employed spouses for whom all relevant variables are observed. For an individual to be included in our dual-earner sample, neither is the partner required to work full-time nor has an hourly wage rate to be observed for the partner. As these requirements have to be met only for the individual himself, our dual-earner sample contains more men than women, mostly because part-time rates are higher for women.[16]

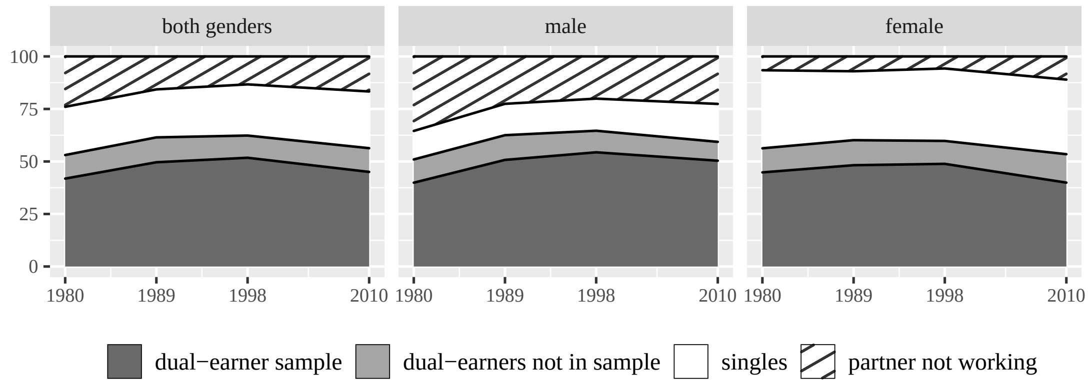
The left panel of Figure 2.1 shows the shares of workers in dual-earner households and of single earners within the population of full-time workers. The two gray areas represent workers in dual-earner households. The lighter gray areas indicate the workers for whose partners information is missing or whose partners work outside the civilian non-farm sector and who are thus not part of the regression samples. The two white areas represent workers who are the sole earners in their households, either because they have no partner (unhatched area) or because their partner does not work for pay (hatched area). Somewhat more than every second full-time worker is part of a dual-earner couple and single earners constitute slightly less than 50% of full-time workers. Within the group of single earners, the share of singles increases over time. The middle and right panels of Figure 2.1 show the shares of the different groups separately for men and women. For both genders, workers in dual-earner couples are about 50% of all full-

[14] As is standard, full-time is defined as being employed and working at least 35 hours per week.

[15] In later evaluations, we also consider samples of singles (defined as individuals with no partner, neither married nor cohabiting) and single earners (defined as individuals who are the sole earner in their household independent of marital or cohabitation status).

[16] Appendix 2.C provides additional details on the sample selection.

Figure 2.1. Composition of full-time workers by household status.



Notes: Shares of singles, single-earners and workers in dual-earner households in population of full-time workers by year. Gray areas represent workers in dual-earner households with dark gray indicating dual-earner sample for subsequent analysis and lighter gray indicating workers whose partners have missing information or work outside the civilian non-farm sector. White areas represent workers who are the sole earners in their households, either because they have no partner (unhatched) or because their partner does not work for pay (hatched).

time workers. Within the group of single earners, differences between genders are more pronounced. There are only few female workers who have a non-working partner.[17]

Regarding selectivity, we will show that our dual-earner sample is similar to the Blau-Kahn sample with respect to trends in the gender wage gap and in key explanatory variables as well as with respect to results from standard Oaxaca-Blinder decompositions. This is important as it ensures that differences between the results of our extended Oaxaca-Blinder decomposition and the standard decomposition are in fact due to the methodological extension and are not driven by the different samples.

Hourly wage rates and explanatory variables. The hourly wage rate is calculated as annual labor earnings divided by annual hours worked. The preferred specification of the wage equation in Blau and Kahn (2017) uses as explanatory variables the individual's education (years of schooling and dummy variables for bachelor and master degrees) and experience (years of full-time experience, years of part-time experience), race or ethnicity, Census region dummies, a dummy for living in a metropolitan area, as well as variables containing job information, such as industry (15 two-digit groups, 2000 Cen-

[17] Our dual-earner sample contains 902 (in 1980), 1,312 (in 1989), 1,288 (in 1998) and 1,179 (in 2010) men as well as 668 (in 1980), 991 (in 1989), 1,039 (in 1998), 977 (in 2010) women. In the sample of full-time workers, there are 2,261 (in 1980), 2,585 (in 1989), 2,369 (in 1998), and 2,341 (in 2010) men as well as 1,491 (in 1980), 2,055 (in 1989), 2,126 (in 1998), 2,447 (in 2010) women.

sus classification), occupation (21 two-digit groups, 2000 Census classification), union coverage, and whether the respondent is working for the government. For our extended decomposition, we augment the wage equation by the partner's education, experience, and job information.[18]

Oaxaca-Blinder decompositions do not aim at identifying causal relations between variables but are merely accounting tools used to assess how much pay differences can be related to differences in observable characteristics. In our context, it is nonetheless important to discuss in how far the additional explanatory (partner) variables added to the wage equation in our extended Oaxaca-Blinder decomposition reflect *choices* of the dual-earner couple. Recall that our theoretical mechanism runs from characteristics of the individual spouses to wage-relevant (joint) choices of the couple. While almost all of the explanatory variables described above constitute choices, it makes sense to consider most of them characteristics from the perspective of our model. Education is typically chosen before couple households form and is hence not subject to the joint decision making which is key to our mechanism. Empirical evidence shows that industry and occupation are rarely switched and doing so entails substantial costs, see, e.g., Kambourov and Manovskii (2009), Artuç and McLaren (2015) and Cortes and Gallipoli (2018). Thus, individuals' initial choices on industry and occupation, which for most individuals occur before formation of the marriage, are of significant importance during marriage but usually not subject to joint decision making. Arguably, the accumulation of work experience and the lack thereof occurs during the course of the marriage and is largely a decision of the couple that may take into account anticipated differences in returns to experience. However, one can also argue that career interruptions are mostly caused by child births and the absence of affordable child care and that their distribution within the couple is to a large extent driven by norms (Bertrand, Kamenica, and Pan 2015; Blau et al. 2020). In our baseline set-up, we include experience in the set of control variables which preserves direct comparability to Blau and Kahn (2017) and facilitates the interpretation of the unexplained gap.[19] We will also consider specifications where

[18]The partner's race or ethnicity, region of residence, and metropolitan status are not included due to collinearity to the corresponding information for the individual itself.

[19]To shed light on mechanisms behind the wage gap, we have also considered a specification without experience. In this specification, the explained wage gap is reduced but by less than the wage differences that the model including experience assigns to this factor. This indicates that experience is both a mediator of some other included wage determinants or either a wage determinant in itself or a mediator of unobservable factors such as discrimination. Quantitatively, the role of experience as a

we use predicted experience to address potential endogeneity. Finally, union coverage is mostly determined by the choice of employer and hence a joint decision of the couple from the viewpoint of our model. We nevertheless include this variable in the set of explanatory variables in order to maintain full comparability to Blau and Kahn (2017).

Descriptive statistics. The first part of Table 2.1 shows average log wage rates by gender as well as the gender wage gap for our dual earner sample (columns (1) through (4)) as well as for the sample of full-time workers independent of household type used by Blau and Kahn (2017) (columns (5) through (7)). Both samples display the substantial decrease of the gender wage gap and the slowing down of the convergence in later years (Goldin 2014). This indicates that selectivity of the dual-earner sample is of moderate importance in this respect.

The table also summarizes education and full-time experience by gender for both samples together with developments of other determinants of wages related to job information.[20] Both samples show the well-known reversal of the gender gap in education and women's catching up in terms of full-time experience. Women less often than men work in managerial occupations but more often in professional occupations. In both types of occupations, female shares are increasing over time. Despite their strong representation in professional occupations in general, women are still the minority in the high-paying professional occupations traditionally dominated by men, such as lawyers and doctors.[21] Union coverage rates and gender differences therein are similar in both samples with women being less frequently covered by collective-bargaining agreements than men in early years and similarly often in recent years. Overall, we conclude that the dual-earner sample and the Blau-Kahn sample have similar properties regarding gender gaps in wage determinants and their trends. Table 2.1 also shows that pay-relevant characteristics are positively correlated between spouses in dual-earner couples. This supports the assortative-mating assumption applied in Section 2.4.2.[22]

mediator of other observable determinants seems to be limited, amounting to less than one fifth of the wage differences assigned to differences in experience. This supports our handling of experience as a characteristic in the baseline specification.

[20] The underlying categorization of occupations and industries follows Blau and Kahn (2017).

[21] High-pay professional occupations are professional occupations other than nurses and non-college teachers.

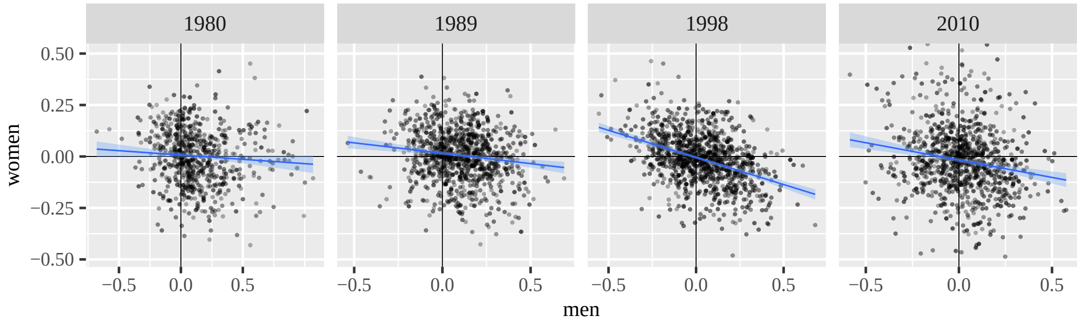
[22] The correlation in full-time experience is mostly driven by the high correlation in spouse's age. The conditional correlation is relatively small.

Table 2.1. Log wages, human capital, and job attributes by gender, year, and sample.

	Dual-earner sample				Blau-Kahn sample		
Year	Men (1)	Women (2)	Difference (3)	$\mathrm{Corr}(x_i, x_{-i})$ (4)	Men (5)	Women (6)	Difference (7)
Log Wage Rates							
1980	3.08	2.65	0.43	0.36	3.08	2.60	0.48
1989	3.09	2.77	0.33	0.39	3.06	2.76	0.30
1998	3.16	2.89	0.26	0.28	3.11	2.85	0.26
2010	3.29	3.04	0.25	0.37	3.24	3.00	0.23
Years of schooling							
1980	13.09	13.05	0.04	0.61	13.13	12.96	0.17
1989	13.65	13.54	0.11	0.55	13.57	13.51	0.06
1998	14.06	14.16	-0.10	0.53	13.93	13.98	-0.05
2010	14.32	14.62	-0.31	0.50	14.32	14.48	-0.16
Bachelor (in %)							
1980	17.25	15.22	2.03	0.33	17.32	15.99	1.33
1989	19.37	16.57	2.80	0.26	20.00	18.05	1.95
1998	23.55	24.00	-0.45	0.25	23.42	22.48	0.94
2010	24.83	26.52	-1.69	0.27	26.24	24.78	1.46
Advanced degree (in %)							
1980	8.33	6.86	1.47	0.32	8.12	6.09	2.04
1989	10.09	8.27	1.81	0.30	9.63	8.35	1.28
1998	11.99	12.24	-0.25	0.32	11.05	10.20	0.85
2010	13.41	17.86	-4.46	0.30	12.90	15.73	-2.83
Years of full-time experience							
1980	21.92	13.08	8.83	0.51	20.32	13.51	6.81
1989	20.45	13.48	6.96	0.42	19.15	14.72	4.44
1998	21.46	15.15	6.31	0.51	19.77	15.93	3.84
2010	18.95	15.06	3.89	0.66	17.80	16.35	1.44
Managerial jobs (in %)							
1980	21.42	8.92	12.50	0.10	21.52	9.18	12.34
1989	22.04	11.96	10.08	0.13	20.87	10.96	9.91
1998	22.56	16.47	6.09	0.11	21.87	15.40	6.47
2010	19.21	16.81	2.40	0.15	18.35	16.20	2.15
Professional jobs (in %)							
1980	17.83	23.17	-5.34	0.26	17.08	21.80	-4.72
1989	19.34	25.05	-5.72	0.23	19.45	26.06	-6.61
1998	21.41	28.49	-7.08	0.19	20.47	26.89	-6.42
2010	21.88	30.13	-8.26	0.25	21.70	31.09	-9.39
High-pay professional jobs (in %)							
1980	14.32	9.53	4.79	0.15	14.60	10.10	4.50
1989	16.45	13.38	3.06	0.17	17.32	14.11	3.21
1998	18.18	13.59	4.59	0.16	17.61	13.14	4.48
2010	18.37	15.04	3.33	0.14	18.59	17.78	0.81
Collective-bargaining coverage (in %)							
1980	34.36	19.97	14.39	0.20	34.51	21.14	13.37
1989	25.23	18.08	7.15	0.27	25.46	19.40	6.05
1998	21.88	20.10	1.78	0.20	21.44	18.22	3.23
2010	17.71	19.44	-1.73	0.24	17.45	18.95	-1.50

Notes: Descriptive statistics for selected characteristics. Columns (1), (2), (5), and (6) show gender-specific weighted averages. Columns (3) and (7) show male average minus female average. Column (4) shows correlation between own and partner characteristics in sample of men in dual-earner couples.

Figure 2.2. Predicted wages relative to potentials.



Notes: Differences between predicted log wage, $\widehat{w}_i = \widehat{b}^{ext}_{1,g(i)} X_i + \widehat{b}^{ext}_{2,g(i)} X_{-i}$, and counterfactual log wage, $\widetilde{w}_i = \widehat{b}^{ext}_{1,g(i)} X_i + \widehat{b}^{ext}_{2,g(i)} X_i$, proxying potentials. Each dot represents one couple (male partner on horizontal axis, female partner on vertical axis).

2.5.2 Wage regressions

Before turning to wage-gap decompositions, we briefly consider the results of the wage regressions. Table 2.D.1 in Appendix 2.D shows the estimated coefficients. Here, we present important summary information because most characteristics are non-metric or enter the regressions non-linearly making the coefficients little informative.

The scatterplots in Figure 2.2 show, for each year, predicted deviations from earnings potentials within individual couples. For the figure, we use our empirical model to predict counterfactual wage rates that would arise if spouses' careers were treated equally by families, i.e., if an individual were married to a partner with identical characteristics, $X_{-i} = X_i$. Hence, we calculate

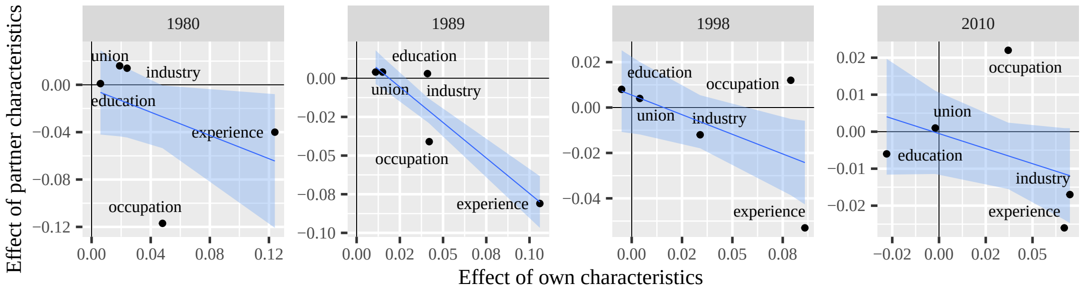
$$\widetilde{w}_i = \widehat{b}^{ext}_{1,g(i)} X_i + \widehat{b}^{ext}_{2,g(i)} X_i.$$

Note that, in our theoretical model, $\widetilde{w}_i$ is a linear function of the log earnings potential $\log \psi_i$ and unobservable terms, see (2.6). This counterfactual wage rate has to be distinguished from the prediction based on the partner's actual characteristics X_{-i},

$$\widehat{w}_i = \widehat{b}^{ext}_{1,g(i)} X_i + \widehat{b}^{ext}_{2,g(i)} X_{-i}$$

and the figure shows $\widehat{w}_i - \widetilde{w}_i$ for men on the horizontal axis and for women on the vertical axis. The relation between the two deviations is negative, which means that if the wife realizes a high wage relative to her potential, the husband's wage tends to be

Figure 2.3. Average effect on men's wage of improving their own and their partners' characteristics.



Notes: Effect of own and partner characteristics on male wages by variable group. Horizontal axis separates $\widehat{b}^{ext}_{own,m} \cdot (\overline{X}_m - \overline{X}_f)$ into parts related to education, experience, industry, occupation, and union coverage. Vertical axis separates $\widehat{b}^{ext}_{partner,m} \cdot (\overline{X}_m - \overline{X}_f)$ analogously. Fitted regression line with $\pm$ one standard error.

low relative to his potential and vice versa. This is a first piece of evidence suggesting the importance of the career-priorization channel in the data.

Yet, while the predicted deviations from earnings potentials within individual couples shown in Figure 2.2 reflect the joint influence of all characteristics, one should not expect that the career-prioritization channel is equally important for all wage characteristics. For this reason, Figure 2.3 considers the wage effect of own and partner characteristics one by one, distinguishing between the five core characteristics education, work experience, industry, occupation group, and union coverage.[23] On the horizontal axis, we show the conditional wage difference between the average man and a counterfactual man that is like the average woman *in the respective characteristic*. On the vertical axis, we show the conditional wage difference between the average man and a counterfactual man *whose wife* is like the average man in this characteristic. According to the career-prioritization channel, the first number (own characteristic) and the second number (partner characteristic) should have the opposite sign. Put differently, this channel implies that the points in the figure should lie in the upper-left or lower-right quadrant. The distance of the points from the origin indicates the difference between men and women in the respective characteristic.

The results in Figure 2.3 show that, in all years, there is a downward slope of the points and the points of the characteristics in which men and women differ strongly

[23]Specifically, we perform counterfactual experiments where we vary one of these characteristics and use the estimated wage equation for men from our baseline analysis to predict the associated change on men's average wages.

Table 2.2. Change in average wages relative to status quo in counterfactual where individuals marry identical partners.

	1980	1989	1998	2010
men	13.6	10.4	4.0	1.6
women	0.1	0.6	-1.4	-2.3

Notes: Average difference between observed log wage, w_i, and counterfactual log wage, $\widetilde{w}_i = \widehat{b}^{ext}_{1,g(i)} X_i + \widehat{b}^{ext}_{2,g(i)} X_i$, by year and gender.

are mainly located in the lower-right quadrant.[24] Experience, as the most prominent example, satisfies two important conditions. First, men and women differ significantly in this characteristic. Second, the effect of the partner trait is such that men's wages decline in their wives' work experience. By contrast, the effects of education seem to be better described by the spill-over channel. In general, partner education seems to affect wages in the same direction as one's own education does. Yet, education is not as important for the gender wage gap as other characteristics because men and women do not differ strongly from each other in terms of their average education. Thus, the career-prioritization channel is not the dominant force for all characteristics, but for those characteristics that are important for decomposing the wage gap because of large gender differences in them.

As a final evaluation before we turn to the decompositions, we calculate, by year and gender, the predicted change in average wage rates that would result if families stopped prioritizing the careers of the designated primary earners but instead weighted both spouses' careers equally in their decisions. Put formally, we determine the change in gender-specific average wages resulting from every individual changing from the actual log wage rate w_i to the counterfactual wage rate $\widetilde{w}_i$. The results are shown in Table 2.2.

The estimated wage equation predicts that men in dual-earner marriages would earn lower wage rates if their wives had the same characteristics as they themselves, in line with the career-prioritization channel. Men's wages seem to be fostered by households prioritizing their careers. If their wives had the same characteristics and, hence, more similar earnings potentials, the incentives for households to prioritize men's careers

[24] This means that men earn higher wages, on the one hand, because they are different from their wives in these characteristics. On the other hand, their wages would go down if their wives were identical to them in these characteristics.

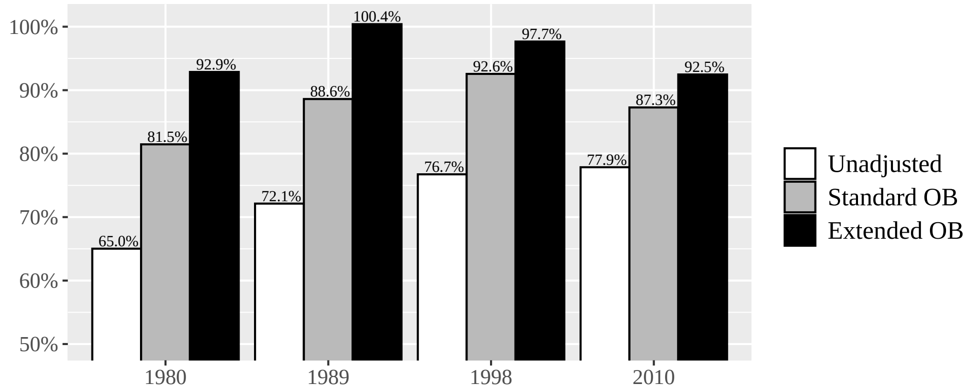
would be smaller and, in line with this, men's predicted wages decline. In the early years of our sample, this channel makes up for more than 10% of men's wage rates. For women, the effects are smaller, but these estimates should be viewed with caution due to the particularities of female labor supply such as selection that are likely to affect the estimated female wage equation more strongly than the one for men. In the later years, quantitative differences between actual and counterfactual wage rates become smaller for men. However, even for the year 2010, where it is 1.6% for men and 2.3% for women, the combined 4 percentage point contribution to the gender wage gap is one sixth of the total wage gap and roughly half of what remains unexplained in the standard decomposition of Blau and Kahn (2017).

2.5.3 Baseline decomposition

Baseline results. Figure 2.4 shows the results of Oaxaca-Blinder decompositions in the dual-earner sample. Following Blau and Kahn (2017), we display the inverse exponential of the raw wage gap Δ and of the unexplained wage gap $\widehat{\Delta}|_b$, hence the level of the gap in log points can (approximately) be seen in the figure as the difference between the bars and 100%. The inverse exponential of the raw gap, $1/\exp(\Delta)$, is the unadjusted ratio of women's mean wage rate to the one of men. The inverse exponential of the unexplained gap is the adjusted wage ratio, i.e., the ratio of the average wage women actually earn and the average wage women would earn if their characteristics were priced in the same way by the labor market as men's (i.e., if they had the same coefficients as men). The white bars show the unadjusted wage ratios, i.e., correspond to the raw gender wage gaps. The gray bars show the results from the standard Oaxaca-Blinder decomposition. The black bars show the results from our extended approach, where we augment the wage equation by the characteristics of the partner.

The white bars show the substantial closure of the gender wage gap during the 1980s and the slowing down of the convergence in later years. The gray bars show that a standard Oaxaca-Blinder decomposition explains a substantial amount of the gender wage gap, as discussed by Blau and Kahn (2017). However, a substantial gap in adjusted wages remains. The adjusted wage ratio stagnates at around 90% from 1989 on. Put differently, a gap of roughly 10 percentage points, which corresponds to between one third and three fifths of the raw gap, remains unexplained by a standard Oaxaca-Blinder

Figure 2.4. Comparison of standard Oaxaca-Blinder (OB) decomposition and extended decomposition using partner characteristics, dual-earner sample: Log female to male wage ratio, unadjusted and adjusted for covariates.



Notes: White bars show $1/\exp(\Delta)$, where Δ is raw gender wage gap, see (2.10). Gray bars show $1/\exp((\widehat{\Delta}|_b)^{std})$, where $(\widehat{\Delta}|_b)^{std}$ is unexplained wage gap of standard decomposition, see (2.12). Black bars show $1/\exp((\widehat{\Delta}|_b)^{ext})$, where $(\widehat{\Delta}|_b)^{ext}$ is unexplained wage gap of extended decomposition, see (2.14).

decomposition. Note that the results for our dual-earner sample are similar to the ones for the Blau-Kahn sample. Specifically, in their full specification, Blau and Kahn (2017) report adjusted wage ratios of 79.4%, 92.4%, 91.4% and 82.1%, respectively. Thus, moving from the Blau-Kahn sample to our sample of dual-earner households does not affect the results of the standard Oaxaca-Blinder decomposition substantially. This mitigates concerns of selectivity of the dual-earner sample.

The most important result of our analysis is that, in all years, the adjusted wage ratios using our extended Oaxaca-Blinder decomposition (black bars) are substantially larger than the adjusted wage ratios indicated by the standard approach (gray bars), in line with the predictions of our model with a dominant career-prioritization channel. In 1989, our extended Oaxaca-Blinder decomposition explains 100% of the gap. For the other years, a small unexplained gap remains but it is considerably smaller than the gap that remains unexplained by the standard decomposition. Thus, accounting for partner characteristics allows to explain a substantially larger part of the gender wage gap.

Figure 2.4 also shows that the part of the gap that remains unexplained by the standard Oaxaca-Blinder decomposition (roughly the difference between the gray bars and 100%) declines substantially over time. One possible interpretation is that the closure of the wage gap between 1980 and 2010 may to a discernible part be attributed to declining discrimination. This interpretation, however, is not supported by our extended Oaxaca-Blinder decomposition which delivers a roughly constant unexplained gender gap amounting to about 7 percentage points in both 1980 and 2010.[25]

For 1989, we can understand gender differences in wages as simply reflecting gender differences in pay relevant characteristics when we take into account the role of partner characteristics. The results for the other years indicate that unobservable factors such as discrimination or differences in noncognitive skills do contribute to the wage gap to some extent, but a standard Oaxaca-Blinder decomposition understates substantially the extent to which the wage gap is related to observable characteristics.

2.5.4 Sensitivity

We have performed a number of sensitivity checks to corroborate the robustness of our main results. Table 2.3 summarizes the explained wage gaps $\widehat{\Delta}|_X$ obtained in various sensitivity analyses for both, the standard and the extended decomposition. The first line repeats, in this format, the results of the baseline specification for convenience.

Sample. As alternative samples, we consider a narrower age range (line 2) as well as a sample that, compared to our baseline sample of dual earners working full time and full year, also includes part-time (line 3) and part-year (line 4) workers. In all three samples, we find for all years that the extended decomposition explains a larger part of the wage gap through observable characteristics.

Selection. Selection of women into employment can induce two biases in the decomposition. First, the true gap in offer wages might be larger than the gap in observed realized wages when, systematically, women with low wage offers opt out of the labor

[25] Blau and Kahn (2006) study the slowdown in the closure of the gender wage gap since the 1990s and highlight a substantial slowdown in the closure of the unexplained wage gap as a main driver. We see this phenomenon also in our standard decompositions where the unexplained gap closes substantially between 1980 and 1989 but only moderately between 1989 and 1998. Our extended decompositions provide a new perspective on this: also here, the unexpected gap closes substantially in the 1980s but is closed by 1989. Hence, it is not surprising that there is not much convergence during the 1990s. The closure of the unexplained gap in the standard decomposition can be understood as declining career prioritization (overlooked by standard decompositions) in favor of men as women caught up in terms of education and other measures of human capital. In both types of decompositions, we see the unexplained gap widening in the 2000s, mirroring the almost standstill of the wage gap in presence of continuing convergence of the covariates.

Table 2.3. Sensitivity analysis.

			1980	1989	1998	2010
1.	baseline	$(\widehat{\Delta}\vert_X)^{std}$	0.225	0.206	0.187	0.114
		$(\widehat{\Delta}\vert_X)^{ext}$	0.356	0.331	0.241	0.172
2.	age range 30-60	$(\widehat{\Delta}\vert_X)^{std}$	0.239	0.183	0.171	0.108
		$(\widehat{\Delta}\vert_X)^{ext}$	0.370	0.290	0.234	0.177
3.	including part-time workers	$(\widehat{\Delta}\vert_X)^{std}$	0.277	0.250	0.216	0.130
		$(\widehat{\Delta}\vert_X)^{ext}$	0.459	0.375	0.277	0.174
4.	including part-year workers	$(\widehat{\Delta}\vert_X)^{std}$	0.224	0.218	0.182	0.119
		$(\widehat{\Delta}\vert_X)^{ext}$	0.343	0.332	0.230	0.160
5.	including households	$(\widehat{\Delta}\vert_X)^{std}$	0.346	0.294	0.281	0.218
	with non-working wives	$(\widehat{\Delta}\vert_X)^{ext}$	0.614	0.433	0.433	0.252
6.	education and experience	$(\widehat{\Delta}\vert_X)^{std}$	0.215	0.214	0.197	0.120
	as categorical variables	$(\widehat{\Delta}\vert_X)^{ext}$	0.371	0.291	0.241	0.177
7.	interaction	$(\widehat{\Delta}\vert_X)^{std}$	0.224	0.202	0.194	0.119
	education × experience	$(\widehat{\Delta}\vert_X)^{ext}$	0.350	0.323	0.248	0.183
8.	interaction	$(\widehat{\Delta}\vert_X)^{std}$	0.226	0.207	0.190	0.116
	education × union status	$(\widehat{\Delta}\vert_X)^{ext}$	0.357	0.332	0.244	0.172
9.	interaction	$(\widehat{\Delta}\vert_X)^{std}$	0.229	0.217	0.173	0.099
	industry × experience	$(\widehat{\Delta}\vert_X)^{ext}$	0.361	0.323	0.248	0.121
10.	joint estimation of male	$(\widehat{\Delta}\vert_X)^{std}$	0.231	0.210	0.191	0.121
	and female wage equation	$(\widehat{\Delta}\vert_X)^{ext}$	0.269	0.228	0.224	0.140

Notes: Explained wage gaps $\widehat{\Delta}|_X$ in different specifications of standard and extended decomposition. Line 1 repeats baseline results. Lines 2-5: sample changed as indicated relative to baseline. Lines 6-9: explanatory variables extended as indicated relative to baseline. Line 10: structural equation model where both partners' wages depend on latent earning

force. Second, the sample of employed women may have different characteristics than a full sample of all women. To account for these potential biases, Oaxaca-Blinder decompositions have been extended by corrections for selection (e.g., Neuman and Oaxaca 2004; Machado 2017; Maasoumi and Wang 2019) while other papers have used information from previous or subsequent employment spells of the same individual (Blau and Kahn 2006; Olivetti and Petrongolo 2008). We take a pragmatic approach and exploit that the coefficients of the male wage equation are not subject to selection of women into the labor force and that the average characteristics of all women (independent of labor-force participation) can be calculated from observables. Hence, we can quantify the wage differences (in log points) that can be related to observable differences between men and all women in couple households – though not a gap in offer wages to which we could relate it (in percent). For this exercise, we extend our baseline sample by those couple households where only the male is working. For non-working women, we use the job information on occupation and industry regarding their last or subsequent employment spell. From this sample, we estimate the male wage equation and multiply the resulting coefficients with the average gender differences in characteristics. The results are shown in line 5 of Table 2.3. Also in the sample including non-participating women, our extended approach assigns considerably larger differences in pay to observable factors than does the conventional approach that omits partner characteristics.

Linearity. A potential shortcoming of the Oaxaca-Blinder approach is its linearity assumption and non-parametric wage equations have been estimated as alternatives (DiNardo, Fortin, and Lemieux 1996; Frölich 2007; Mora 2008, and Ñopo 2008). Our baseline specification of the wage equation follows Blau and Kahn (2017) and is mostly non-parametric as all variables except years of schooling and the experience variables are categorical. As a robustness check, we have also treated these variables as categorical (experience rounded to full years). Line 6 in Table 2.3 shows that this affects our results only mildly. Relatedly, the Oaxaca-Blinder approach usually does not account for interactions between wage determinants. For this reason, it might overlook for example the age-specific wage premium to education (Bhuller, Mogstad, and Salvanes 2017). The results in line 7 of Table 2.3 refer to a specification where we included interaction terms of years of schooling with years of full and part time experience. In line 8, we allow for an interaction between education and union status to account for union wage premia differing along the skill distribution. In line 9, we include interaction terms between years of experience and industry dummies to take into account that experience is not valued the same in every job. In all three variations, the results are similar to those of our baseline specification.

Women's wages. One of the main advantages of Oaxaca-Blinder and similar decomposition approaches is that they can quantify the importance of observable differences between men and women for wage gaps without having to estimate a wage equation for women. This way, these approaches limit their exposure to challenges like selection that would likely bias estimates for a female wage equation. Yet, our model implies that wages in a marriage are interdependent and, thus, ignoring the determination of women's wages is tantamount to not using information that might improve the estimation of the wage equation for men. Thus, there is a trade-off between, on the one hand, a potentially inefficient estimation of men's wage equation and, on the other hand, making the analysis subject to biases stemming from estimating women's wage equation. For comparability to the literature, we chose to estimate only men's wage equation in the baseline analysis. For completeness, we now estimate both men's and women's wage equations jointly, taking into account the cross-equation restrictions our model implies because characteristics affect wages through the earnings potentials as mediators that appear in both men's and women's wage equations. In this specification, we first determine estimates for the latent earnings potentials and then decompose them into four components, education, experience, job information, and other. Line 10 of Table 2.3 shows the results of a wage-gap decomposition based on the estimates from this specification. Also here, we find our main result confirmed: explained gaps are larger for extended decompositions that take into account partner characteristics.[26]

2.5.5 Implications for households with a single earner

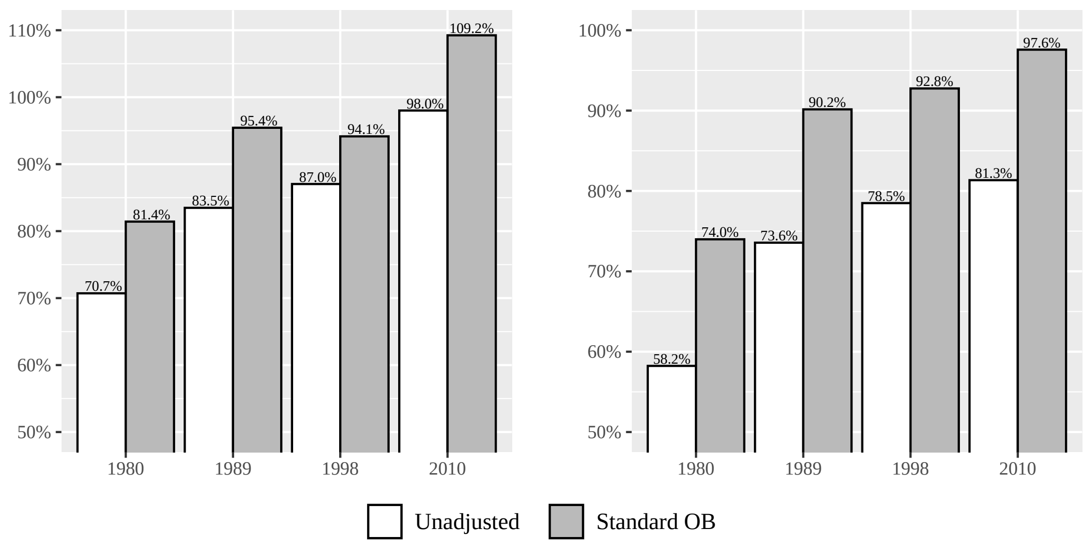
Our extended Oaxaca-Blinder decomposition is motivated by joint decision making in dual-earner households and, in our model, we emphasized that joint decision making induces career prioritization. Given that the model mechanism that leads to the bias in a standard Oaxaca-Blinder decomposition is absent for bachelor households or couple households with a single earner, our model implies that a standard Oaxaca-Blinder decomposition should explain larger shares of the gender wage gap in samples of bachelor workers or single earners in general.

To investigate this relation, Figure 2.5 shows results for singles (defined as individuals with no partner, neither married nor cohabiting, Figure 2.5a) and single earners (defined as individuals who are the sole earner in their household independent of marital

[26]With all caution due to the challenges associated with estimating women's wage equation, this exercise can be used to test for symmetry in career prioritization across genders. On average, the wage effect of the partner's earnings potential is about one tenth as strong as the effect of one's own earnings potential. Specifically, the relative effect size is 0.0969 (standard error 0.0314) for men and 0.1048 (0.0402) for women. A t-test comparison gives a p-value of 0.83, hence not rejecting symmetry.

Figure 2.5. Standard Oaxaca-Blinder (OB) decomposition in a sample of singles (left) and single earners (right): Log female to male wage ratio, unadjusted and adjusted for covariates.

(a) Sample of singles. **(b)** Sample of single earners.



Notes: White bars show $1/\exp(\Delta)$, where Δ is raw gender wage gap, see equation (2.10). Gray bars show $1/\exp((\widehat{\Delta}|_b)^{std})$, where $(\widehat{\Delta}|_b)^{std}$ is unexplained wage gap of the standard decomposition, see equation (2.12).

or cohabitation status, Figure 2.5b).[27] Figure 2.5a shows that the standard Oaxaca-Blinder decomposition explains very large shares of the gender wage gap among singles. Importantly, the unexplained wage gap between male and female singles is substantially smaller than the one a standard Oaxaca-Blinder decomposition suggests in a sample of dual-earner couples or in a sample of all workers. Figure 2.5b reveals a similar pattern for single earners in general. Also here, the standard Oaxaca-Blinder decomposition explains large shares of the gender wage gap, ranging to close to 100%. These results support that a standard Oaxaca-Blinder decomposition underestimates the part of the gender wage gap attributable to observable differences between men and women due to its neglect of the role of partner characteristics for wage rates of workers in dual-earner couples.

[27] The sample of singles contains 307 (in 1980), 386 (in 1989), 362 (in 1998) and 423 (in 2010) men; and 554 (in 1980), 674 (in 1989), 733 (in 1998) and 869 (in 2010) women. In the single-earner sample, there are 1109 (in 1980), 969 (in 1989), 838 (in 1998) and 952 (in 2010) men and 652 (in 1980), 819 (in 1989), 855 (in 1998) and 1,139 (in 2010) women.

2.5.6 Wage effect of partner's experience and role of children

Our results show that experience is a key characteristic for explaining the gender wage gap, as it satisfies two important conditions. First, men and women differ significantly in this characteristic. Second, the effect of the partner trait is such that men's wages decline in their wives' work experience. The latter condition is important because only when the career prioritization channel is dominant does the explained part of the wage gap increase when the partner variable is added. Especially in the case of work experience, however, one might debate to what extent the OLS estimator reflects the actual effect of a wife's work experience on her husband's wage as reverse causality might be a threat. Households that report high incomes due to, for example, unobserved ability of the husband, and thus a high wage for him, may be more likely (through a conventional income effect) to interrupt the wife's career, e.g., so that she can provide childcare or take on other family responsibilities. To account for this, we therefore tried to isolate components of work experience that are as independent of wages as possible.

As a first specification, we use age, years of education, years of education of the partner, and information on the number and ages of children in the household to predict years of full-time work experience.[28] We then used these predictions in place of the actual work experience of female partners when estimating the wage equation for men. As a second, alternative, specification, we use the number of brothers and sisters of husband and wife, in combination with age and education, as predictors for women's experience. This specification acknowledges the potential endogeneity of fertility. By exploiting intergenerational persistence in family values and fertility aspiration, it isolates exogenous variation in a couples' number of children which then affects the accumulation of experience.[29]

[28]We find that work experience can be predicted relatively well with the variables used. For men, R-squares range from 0.8 to 0.9, with even a minimum specification with linear effects of age and years of education alone reaching these values and information on children contributing little to the predictive power of work experience. For women's work experience, by contrast, children are substantially more important, and they allow explaining up to 60% of the variation in women's work experience. Thus, there remains unexplained variation–women of the same age and with the same number of children have different levels of work experience–that could potentially be driven by a response to their husbands' wages. We eliminate this part of the variation by using predicted work experience in the estimation of the wage equation.

[29]Since information on siblings of reference persons and spouses is not available in 1981, we do not perform these estimations for this year.

Table 2.4 shows the marginal effects of an additional year of work experience (their own or their partners') on men's log wages. The upper block of the table shows the effects implied by our baseline regression which uses actual rather than predicted experience. Predicted experience measures for wives are used in the second and third blocks, respectively. As is well known in the literature, work experience is a quantitatively significant wage determinant. In our sample, an additional year of work experience is associated with a 1 to 2 percent higher wage on average. We now look at the effect of wives' work experience on husbands' wages. In the baseline regression, wives' actual experience is negatively related to husbands' wages, with quantitative effects ranging from 0.3 to 1 percent for an additional year of experience. The two regressions with predicted measures of experience also show a significant negative effect of wives' experience on husbands' wages and the results do not differ strongly from the baseline case. Thus, biases due to reverse causality seem to be moderate. In total, we see that men's wages increase when their wives lack experience. In light of our model, this is because families prioritize men's careers in response to women's lower experience.

These evaluations also help understand the role of children in wage gap decompositions. Since the number of children in family households is the same for both mother and father, by construction children cannot explain a part of the wage gap as a directly included variable. If one includes children as a variable in the decomposition, their impact on women's but not men's experience would result in different coefficients on the number of children and be assigned to the unexplained part of the wage gap accordingly. This is in line with the large contribution of estimated coefficients on children to the unexplained wage gap found by Cortés and Pan (2023). However, if one uses the mediator work experience (in observed or predicted form), the unequal effect of children on the careers of their fathers and mothers moves into the explained part of the wage gap. In fact, in the extended decomposition we propose, it does so in its entirety, while in a standard decomposition the wage effect of children that runs through partners' experience would remain in the unexplained gap. When the effect of children is assigned to the explained part of the gap, the unexplained part is a purified measure of what is potentially due to gender differences in not easily observable characteristics such as personality traits.

Table 2.4. Average marginal effects of an additional year of full-time experience (own and their partners') on men's log wages.

	1989	1998	2010
Model with observed partner's experience			
own experience	0.017	0.010	0.014
	(0.002)	(0.002)	(0.002)
partner's experience	−0.010	−0.007	−0.003
	(0.003)	(0.003)	(0.003)
Model with predicted partner's experience based on children			
own experience	0.017	0.009	0.013
	(0.002)	(0.002)	(0.003)
partner's predicted experience	−0.024	−0.021	−0.014
	(0.013)	(0.011)	(0.007)
Model with predicted partner's experience based on siblings			
own experience	0.018	0.007	0.012
	(0.002)	(0.002)	(0.003)
partner's predicted experience	−0.017	−0.012	−0.014
	(0.008)	(0.006)	(0.005)

Notes: First block shows results from baseline specification of extended wage equation (with observed experience). Second block uses predicted full-time and part-time experience based on number of children, interacted with individual's age and education. Third block uses predicted full-time and part-time experience based on number of siblings of head and wife, interacted with age and education. Standard errors in parentheses.

2.6 Conclusion

We have proposed a simple way to embed family-economics arguments for pay differences between genders into standard decomposition techniques of the wage gap. Our key point is that, for an unbiased decomposition, one has to compare men and women with similar characteristics *and similar partners*. We have set up a theoretical model that allows for a spill-over channel, through which wages depend positively on partner characteristics, and for a career-prioritization channel, through which wages depend negatively on partner characteristics. Standard decompositions ignore both channels and, thus, misestimate the share of the wage gap that is due to observable differences between men and women. When the career-prioritization is the dominant channel from partner characteristics to wages, too small a share is assigned to observable differences. We have proposed an extended decomposition approach that accounts for the role of the family through including partner characteristics. This approach corrects the bias successfully. In U.S. survey data, we found that our extended decomposition explains considerably more of the wage gap than a standard approach – as implied by the career-prioritization channel being an important driver of the wage gap, in line with many papers from the family-economics literature. Policy might exploit the amplification mechanism of career prioritization as policy measures that improve women's earnings potentials can result in families investing more strongly in women's careers, thereby reinforcing the direct effects on the wage gap.

Appendix 2.A Marriage market equilibrium - A two-couple example

The marriage-market equilibrium in our extended model is described by equations (2.7) and (2.8). In this example, we consider a case without the joint investment channel (y constant) which corresponds to the model with only the career prioritization channel. The extended model in the main text has the same qualitative implications.

To illustrate that the marriage market equilibrium does not necessarily display perfect assortative mating along optimal locations, i.e., does not necessarily minimize the wage penalties, consider the following four-person example. Suppose there are two men, Amos and Bert, and two women, Amy and Brenda. The following table 2.A.1 gives their earnings potentials as well as their optimal locations.

Table 2.A.1. Individuals on the marriage market.

name	gender	ψ	a
Amos	male	4	.25
Bert	male	8	.75
Amy	female	2	.75
Brenda	female	6	.25

Note that we have constructed the example in a way that makes it in principle possible that there are no wage penalties. This would arise if Amos married Brenda and Bert married Amy. Yet, this is not the marriage market equilibrium.

The following table 2.A.2 summarizes the potential well-beings of the possible combinations of couples as well as when they choose to be alone (assuming log utility, $u(c) = \log(c)$, for simplicity).

Table 2.A.2. Utility from different matches.

	Amy	Brenda	no partner
Amos	3.18	1.93	1.39
Bert	3.74	2.77	2.08
no partner	1.79	0.69	

Amy wants to marry Bert and Bert wants to marry Amy because this puts both in the best possible situation. Hence, any equilibrium must include a marriage between Amy and Bert as any other situation would leave Bert and Amy with incentives to deviate.

Also Amos would prefer marrying Amy, but left with the choice between marrying Brenda and staying alone, he prefers marrying Brenda. The reverse holds for Brenda who settles for marrying Amos before ending up alone.

Hence, the marriage market consists of the following two households with locations, wages and wage penalties as given in the Table 2.A.3:

Table 2.A.3. Marriage market equilibrium.

Hh	Husband	Wife	ψ_m	ψ_f	a_m	a_f	r	w_m	w_f	penalty$_m$	penalty$_f$
1	Bert	Amy	8	6	.75	.25	0.54	7.63	5.51	4.6%	8.2%
2	Amos	Brenda	4	2	.25	.75	0.42	3.89	1.78	2.8%	11.1%

Both households compromise between the two spouses' careers (i.e., they choose locations between .25 and .75), but they move closer to the husbands' ideal locations. Put differently, both household prioritize the respective husbands' careers resulting in women suffering stronger wage penalties than men. In our example, Brenda has a particularly strong relative penalty because her husband's earnings potential is twice her own.

Appendix 2.B Derivation of the linearized wage equation

Approximation of z_i. We define ϕ such that $\phi^2 = (1-\kappa)\sigma^2$ and $\Lambda_i = \psi_{-i}/\left(\psi_i + \psi_{-i}\right) \cdot (a_{-i} - a_i)$ with derivatives

$$
\begin{aligned}
\frac{\partial \Lambda_i}{\partial \psi_i} &= -\frac{\psi_{-i}}{\left(\psi_i + \psi_{-i}\right)^2} \cdot \left(a_{-i} - a_i\right), \frac{\partial \Lambda_i}{\partial \psi_{-i}} = \frac{\psi_i}{\left(\psi_i + \psi_{-i}\right)^2} \cdot \left(a_{-i} - a_i\right) \\
\frac{\partial \Lambda_i}{\partial a_i} &= -\frac{\psi_{-i}}{\left(\psi_i + \psi_{-i}\right)}, \text{ and } \frac{\partial \Lambda_i}{\partial a_{-i}} = \frac{\psi_{-i}}{\left(\psi_i + \psi_{-i}\right)}.
\end{aligned}
$$

In the point of approximation, these expressions evaluate as $\Lambda^2 = 1/2 \cdot \phi^2 \Rightarrow \Lambda = 2^{-1/2} \cdot \phi$ as well as

$$
\frac{\partial \Lambda_i}{\partial \psi_i} = -\frac{\partial \Lambda_i}{\partial \psi_{-i}} = -\frac{\phi}{2\sqrt{2}}, \quad \text{and} \quad \frac{\partial \Lambda_i}{\partial a_i} = -\frac{\partial \Lambda_i}{\partial a_{-i}} = -\frac{1}{2}.
$$

Applying the approximation gives

$$
\begin{aligned}
&\log z_i = \log\left(1 - \Lambda_i^2\right) \approx \log\left(1 - \Lambda^2\right) \\
&\quad - \frac{2\Lambda}{1-\Lambda^2} \cdot \left(\frac{\partial \Lambda_i}{\partial \psi_i}\left(\psi_i - \psi\right) + \frac{\partial \Lambda_i}{\partial \psi_{-i}}\left(\psi_{-i} - \psi\right) + \frac{\partial \Lambda_i}{\partial a_i}\left(a_i - \overline{a}_i\right) + \frac{\partial \Lambda_i}{\partial a_{-i}}\left(a_{-i} - \overline{a}_{-i}\right)\right)
\end{aligned}
$$

The second line can be rearranged to

$$\begin{aligned}
&= -\frac{\sqrt{2}\phi}{1-\frac{1}{2}\phi^2}\left(\frac{\partial\Lambda_i}{\partial\psi_i}\psi\frac{\psi_i-\psi}{\psi}+\frac{\partial\Lambda_i}{\partial\psi_{-i}}\psi\frac{\psi_{-i}-\psi}{\psi}+\frac{\partial\Lambda_i}{\partial a_i}\left(a_i-\overline{a}_i\right)+\frac{\partial\Lambda_i}{\partial a_{-i}}\left(a_{-i}-\overline{a}_{-i}\right)\right)\\
&\approx -\frac{\sqrt{2}\phi}{1-\frac{1}{2}\phi^2}\left(-\frac{\sqrt{2}\phi}{4}\log\psi_i+\frac{\sqrt{2}\phi}{4}\log\psi_{-i}-\frac{1}{2}\left(a_i-\overline{a}_i\right)+\frac{1}{2}\left(a_i-\overline{a}_i\right)\right)\\
&= \frac{\phi^2}{2-\phi^2}\log\psi_i-\frac{\phi^2}{2-\phi^2}\log\psi_{-i}+\frac{\sqrt{2}\phi}{2-\phi^2}\left(a_i-a_{-i}\right)-\frac{2\phi}{2-\phi^2}\sqrt{(1-\kappa)}\sigma.
\end{aligned}$$

while $\log\left(1-\Lambda^2\right)$ equals $\log\left(1-\frac{1}{2}\phi^2\right)$.

Approximation of y_I. Taking the marginal derivatives of (2.5) gives

$$\frac{\partial y_I}{\partial\psi_i}=\frac{\eta}{2}\left(1-\frac{\psi_{-i}^2-\psi_i\psi_{-i}}{\left(\psi_i+\psi_{-i}\right)^3}\left(a_i-a_{-i}\right)^2\right),\ \frac{\partial y_I}{\partial\psi_{-i}}=\frac{\eta}{2}\left(1-\frac{\psi_i^2-\psi_i\psi_{-i}}{\left(\psi_i+\psi_{-i}\right)^3}\left(a_i-a_{-i}\right)^2\right),$$

and

$$\frac{\partial y_I}{\partial a_i}=-\frac{\partial y_I}{\partial a_{-i}}=-\frac{\eta}{2}\frac{\psi_i\psi_{-i}}{\left(\psi_i+\psi_{-i}\right)^2}2\left(a_i-a_{-i}\right).$$

In the point of approximation, these expressions evaluate as

$$\frac{\partial y_I}{\partial\psi_i}=\frac{\partial y_I}{\partial\psi_{-i}}=\frac{\eta}{2},\ \frac{\partial y_I}{\partial a_i}=-\frac{\partial y_I}{\partial a_{-i}}=-\frac{\eta}{2}\frac{1}{\sqrt{2}}\sqrt{(1-\kappa)}\sigma,$$

and the level of y is

$$\overline{y}=\frac{\eta}{2}\left(2\psi-\frac{1}{2}\left(1-\kappa\right)\sigma^2\right).$$

In the vicinity of $y_I=1$, it holds that $\log y_I\approx y-1$. Hence, we can approximate

$$\begin{aligned}
\log y_I &\approx y-1+\frac{\partial y_I}{\partial\psi_i}\left(\psi_i-\psi\right)+\frac{\partial y_I}{\partial\psi_{-i}}\left(\psi_{-i}-\psi\right)+\frac{\partial y_I}{\partial a_i}\left(a_i-\overline{a}_i\right)+\frac{\partial y_I}{\partial a_{-i}}\left(a_{-i}-\overline{a}_{-i}\right)\\
&= \frac{\eta}{2}\left(\psi_i-\psi\right)+\frac{\eta}{2}\left(\psi_{-i}-\psi\right)-\frac{\eta}{2}\frac{1}{\sqrt{2}}\sqrt{(1-\kappa)}\sigma\left(a_i-\overline{a}_i\right)\\
&\quad+\frac{\eta}{2}\frac{1}{\sqrt{2}}\sqrt{(1-\kappa)}\sigma\left(a_{-i}-\overline{a}_{-i}\right)\\
&\approx \frac{\eta}{2}\log\psi_i+\frac{\eta}{2}\log\psi_{-i}-\frac{\eta}{2}\sqrt{\frac{(1-\kappa)}{2}}\sigma\left(a_i-a_{-i}\right)+\frac{\eta}{2}\left(1-\kappa\right)\sigma^2
\end{aligned}$$

Combining the approximations of z_i and y_I with (2.6) and collecting terms gives (2.9).

Appendix 2.C Additional information on the sample

Shares of singles, single earners, and workers in dual-earner households We start from the group of civilian non-farm full-time workers, excluding the self-employed and individuals who had worked less than 26 weeks. This is a fairly standard group to consider and we follow Blau and Kahn (2017) in the details of the selection of this group (see below). We then split the sample into workers living in dual-earner couples (i.e., those workers who have a partner that also works) and single earners (i.e., those workers who either have no partner or whose partner does not work). When moving to the dual-earner sample, we lose some observations due to missing information about the partner (or because the partner is in the military or works in agriculture). Later on, we isolate yet another subgroup of the single-earner sample, the sample of singles which only contains full-time workers. Also in the single-earner sample, every individual has an observed wage as we do not include the non-working partners of these workers in any regression. Yet, the single-earner sample is larger for men than for women because only few married women work while their husbands do not.

Table 2.C.1 shows the frequencies and shares of singles, single earners, and workers in dual-earner households by year. Across both genders, between 50% and 60% of the observations in our full-time workers sample (1) belong to dual-earner couples (1.1). Around 20% of these observations we lose because some information about the partner is missing which would prevent running the extended decomposition (1.1.2). We also omit those few workers from dual-earner couples whose partners work in the military or in agriculture (1.1.1.2). This leaves between 40% and 55% of all full-time observations in our dual-earner sample (1.1.1.1). The remaining 40% to 50% of observations in the full-time workers sample are single earners (1.2), i.e., workers who are the only earners in their households. Initially, single earners split roughly evenly into singles (1.2.1) and workers with a non-working partner (1.2.2), with the share of singles increasing in later years.

While the numbers discussed before refer to observations, weights must be considered to gauge the shares of the respective samples in the population of full-time workers. The left panel of Figure 2.1 in the main text shows these shares for all workers independent of gender. The two gray areas represent workers in dual-earner households with the

Table 2.C.1. Observation frequencies and shares of singles, single earners, and workers in dual-earner households by year: both genders.

	1980	1988	1998	2010
1 Full-time workers	3752	4640	4495	4788
1.1 thereof: dual earners	1,991 (53%)	2,852 (61%)	2,802 (62%)	2,697 (56%)
1.1.1 thereof: complete partner information	1,580 (79%)	2,314 (81%)	2,342 (84%)	2,171 (80%)
1.1.1.1 thereof: partner in civilian non-farm job *(dual-earner sample)*	1,570 (99%)	2,303 (100%)	2,327 (99%)	2,156 (99%)
1.1.1.2 thereof: partner in military or farm job	10 (1%)	11 (0%)	15 (1%)	15 (1%)
1.1.2 thereof: incomplete partner information	411 (21%)	538 (19%)	460 (16%)	526 (20%)
1.2 thereof: single earners *(single-earner sample)*	1,761 (47%)	1,788 (39%)	1,693 (38%)	2,091 (44%)
1.2.1 thereof: singles *(single sample)*	880 (50%)	1,089 (61%)	1,115 (66%)	1,316 (63%)
1.2.2 thereof: partner not working	881 (50%)	699 (39%)	578 (34%)	775 (37%)

Notes: Full-time workers are civilian non-farm full-time employees, excluding the self-employed and individuals working less than 26 weeks per year, see Table 2.C.2 for details. Percentages give shares of superordinate category.

lighter gray indicating workers for whose partners there is missing information or whose partners work outside the civilian non-farm sector. The two white areas represent workers who are the sole earners in their households, either because they have no partner (unhatched area) or because their partner does not work for pay (hatched area). The weighted shares do not differ substantially from the unweighted ones in Table 2.C.1. Somewhat more than every second full-time worker is part of a dual-earner couple and single earners constitute slightly less than 50% of full-time workers. Within the group of single earners, the share of singles increases over time.

The middle and right panels of Figure 2.1 show the shares of the different groups separately for men and women. For both genders, workers in dual-earner couples are about 50% of all full-time workers. Within the group of single earners, differences between genders are more pronounced. There are only few female workers who have a non-working partner. Put differently, most workers in single-earner couples are men.

Table 2.C.2. Selection of baseline full-time employed sample.

Selection of full-time employed sample	1980	1989	1998	2010	$\sum$
Initial number of observations in PSID	52,694	42,346	35,088	28,988	159,116
After selecting current reference persons & spouses	10,430	11,344	9,974	12,487	44,235
After constraining to age 25 - 65	7,856	9,125	7,962	10,171	35,114
After selecting employed or on temporary leave	5,565	6,989	6,437	7,476	26,467
After taking out self-employed	4,903	6,176	5,716	6,165	22,960
After taking out agriculture and military	4,828	6,113	5,667	6,037	22,645
After selecting obs who worked at least 26 weeks	4,514	5,749	5,466	5,653	21,382
After selecting real hourly wage > 2	4,499	5,733	5,406	5,643	21,281
After accounting for missings in (own)					
industry & occupation	4,303	5,605	5,297	5,623	20,828
union coverage & government	4,290	5,405	5,259	5,531	20,485
experience	4,253	5,302	5,095	5,446	20,096
smsa	4,253	5,291	5,088	5,440	20,072
education	4,252	5,275	5,064	5,430	20,021
After selecting only full-time working	3,752	4,640	4,495	4,788	17,675

Notes: The term "reference person" is synonymous to "head" which is the term used in the earlier waves. Analogously, "spouse" is synonymous to "wife".

On average over all years, their share is about 80%. Hence, in the group of individuals living in single-earner couples, most women do not work (and, thus, do not earn a wage). Yet, our regressions never consider separately the group of workers in single-earner couples (group 1.2.2 in Table 2.C.1), but only in combination with the group of singles (group 1.2.1) as the joint group of single earners (group 1.2). The non-working partners of workers in single-earner couples are never considered in our regressions, except for assigning their partner to the single-earner sample.

Sample selection Table 2.C.2 illustrates the selection of our baseline sample of full-time workers and shows which requirements lead to large drops in the number of observations. Our selection procedure for the sample of full-time workers closely follows Blau and Kahn (2017). The most substantial difference is that we exclude (from the beginning) individuals not currently living in the household (e.g., ex-spouses, deceased individuals), for which we do not have the information asked for in the family questionnaire, and focus on current reference persons ("heads" in the older PSID terminology) and spouses ("wives") throughout. This induces a difference of 96 observations between our baseline sample of full-time workers and the sample considered by Blau and Kahn (2017). A restriction to reference persons and spouses is necessary because the relevant work information is asked only for these groups of household members in the PSID.

Naturally, the age restriction induces a substantial reduction in sample size, reflecting our focus on working individuals, who need to be in working age. The age range applied in our study is already relatively wide and, in a robustness check, we narrow it to 30-60. The restrictions to employed persons and dropping the self-employed are quantitatively important in terms of sample size but also necessary. We lose around 500 observations due to missing experience, a variable that is key to analyzing the gender wage gap. The restriction that affects sample size the most is the restriction to full-time workers, which is usually applied in the wage-gap literature in order to compare female and male workers with similar labor-market commitment.

Appendix 2.D Regression results

Table 2.D.1 shows estimated coefficients for the male wage equation of the extended decompositions. Next to the individual coefficients, we report numbers labeled "male mix vs. female mix". These numbers compare, first, workers with the average male characteristic to workers with the average female characteristic and, second, workers whose partners have the average male characteristic with workers whose partners have the average female characteristic. For experience, we additionally compare workers with mean experience to workers with an additional (marginal) year of experience and we do so for both, own and partner's. For occupation and industry, we document conditional wage differences between major occupation and industry groups (own or partner) and the rest of the sample.

Table 2.D.1. Results of extended wage regressions (standard errors in parentheses).

	1980		1989		1998		2010	
	own	partner	own	partner	own	partner	own	partner
Experience								
Male mix vs. female mix	**0.1246**	**−0.0404**	**0.1059**	**−0.0809**	**0.0853**	**−0.0524**	**0.0667**	**−0.0261**
+1 year full-time experience	**0.0124**	**−0.0073**	**0.0174**	**−0.0091**	**0.0103**	**−0.0044**	**0.0136**	**0.0013**
+1 year part-time experience	**0.0016**	**−0.0078**	**0.0202**	**−0.0007**	**−0.0085**	**0.0022**	**−0.0092**	**0.0016**
yrs full-time exp.	0.0350	−0.0102	0.0322	−0.0082	0.0402	0.0009	0.0345	0.0134
	(0.0058)	(0.0046)	(0.0047)	(0.0044)	(0.0058)	(0.0049)	(0.0068)	(0.0063)
yrs full-time exp. squared	−0.0005	0.0001	−0.0004	−0.0000	−0.0007	−0.0002	−0.0006	−0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
yrs part-time exp.	0.0009	−0.0105	0.0212	0.0020	−0.0116	0.0058	−0.0085	−0.0061
	(0.0097)	(0.0065)	(0.0071)	(0.0053)	(0.0080)	(0.0067)	(0.0100)	(0.0086)
yrs part-time exp. squared	0.0003	0.0004	−0.0003	−0.0003	0.0008	−0.0004	−0.0002	0.0009
	(0.0006)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0007)	(0.0005)

Table 2.D.1. Results of extended wage regressions (standard errors in parentheses) – continued

	1980		1989		1998		2010	
	own	partner	own	partner	own	partner	own	partner
Occupation								
Male mix vs. female mix	**0.0466**	**−0.1201**	**0.0414**	**−0.0433**	**0.0828**	**0.0064**	**0.0271**	**0.0206**
High-pay professional vs. other	**0.0499**	**−0.0207**	**0.1126**	**0.0027**	**0.1783**	**−0.0268**	**0.0624**	**0.0388**
architect	0.0087	−0.3521	0.0221	−0.0064	−0.0198	0.1145	0.0254	0.0474
	(0.0602)	(0.2466)	(0.0510)	(0.1284)	(0.0560)	(0.1455)	(0.0730)	(0.1726)
artist	−0.1706	−0.0463	−0.3097	−0.0820	−0.0758	−0.1283	−0.2883	−0.0361
	(0.1178)	(0.1268)	(0.1083)	(0.0940)	(0.0904)	(0.1001)	(0.1339)	(0.1201)
business specialist	−0.0740	0.0535	0.0682	0.0657	0.0315	−0.0011	−0.2591	−0.1372
	(0.0953)	(0.1056)	(0.0753)	(0.0878)	(0.0890)	(0.0734)	(0.0918)	(0.0834)
cleaning, maintenance	−0.3559	−0.1364	−0.4461	−0.2023	−0.4925	−0.1152	−0.4068	−0.2392
	(0.0929)	(0.0970)	(0.0922)	(0.0815)	(0.0745)	(0.1211)	(0.0953)	(0.1457)
computer, mathematics	0.0917	−0.1657	0.1016	0.1306	0.1288	−0.0621	−0.3211	0.0368
	(0.0950)	(0.1271)	(0.0633)	(0.0884)	(0.0651)	(0.1024)	(0.0674)	(0.1093)
construction, extraction, installation	−0.1270	−0.7353	−0.0927	−0.2405	−0.1313	0.0397	−0.2810	0.0740
	(0.0513)	(0.2117)	(0.0431)	(0.1393)	(0.0479)	(0.1817)	(0.0531)	(0.3079)
financial specialist	−0.1437	0.1500	0.0804	0.0339	−0.0127	0.0444	−0.2965	−0.0778
	(0.0931)	(0.1589)	(0.0898)	(0.0883)	(0.0799)	(0.0869)	(0.1008)	(0.0890)
food, personal care	−0.3843	−0.0779	−0.3798	−0.1578	−0.3918	−0.1218	−0.2250	−0.1859
	(0.1787)	(0.0839)	(0.1281)	(0.0681)	(0.1160)	(0.0709)	(0.1538)	(0.0748)
healthcare	−0.2014	−0.1001	0.0882	−0.0406	−0.0819	−0.0787	−0.0846	−0.0431
	(0.1128)	(0.0743)	(0.1098)	(0.0591)	(0.1241)	(0.0635)	(0.1023)	(0.0701)
healthcare support	−0.2800	−0.2266	−0.5199	−0.0957	−0.8022	−0.2720	−0.5456	−0.2396
	(0.1764)	(0.0864)	(0.2249)	(0.0688)	(0.1850)	(0.0785)	(0.4415)	(0.0885)
lawyer, judge, physician*	−0.3588		−0.0153	−0.2627	0.2261	−0.2126	−0.0064	−0.2754
	(0.1753)		(0.1117)	(0.2266)	(0.1082)	(0.1406)	(0.0986)	(0.2036)
legal assistant, teacher	−0.1089	−0.0230	−0.0936	−0.1300	−0.4591	−0.0407	−0.2294	−0.0925
	(0.0902)	(0.0746)	(0.0828)	(0.0616)	(0.0896)	(0.0615)	(0.1004)	(0.0637)
office, admin. support	−0.2313	−0.0080	−0.2375	−0.0020	−0.3270	−0.0052	−0.3775	−0.0791
	(0.0588)	(0.0590)	(0.0533)	(0.0469)	(0.0571)	(0.0481)	(0.0643)	(0.0526)
postsecondary teacher	−0.1429	−0.1046	−0.0646	0.0962	−0.0093	0.0499	−0.4297	0.2464
	(0.1211)	(0.1421)	(0.1424)	(0.1396)	(0.1381)	(0.1507)	(0.3927)	(0.1450)
production worker	−0.1232	−0.1801	−0.2064	−0.1455	−0.1759	−0.1625	−0.3908	−0.1608
	(0.0471)	(0.0760)	(0.0427)	(0.0701)	(0.0493)	(0.0756)	(0.0608)	(0.0910)
protective services	−0.3346	−0.0221	−0.1923	−0.3740	−0.2317	−0.0920	−0.2442	−0.1863
	(0.1021)	(0.1644)	(0.0722)	(0.1465)	(0.0765)	(0.1251)	(0.0749)	(0.1374)
sales	−0.1207	−0.0290	−0.1245	−0.0536	−0.0675	−0.0898	−0.0879	0.0074
	(0.0621)	(0.0711)	(0.0482)	(0.0548)	(0.0512)	(0.0546)	(0.0569)	(0.0707)
scientist	−0.1053	0.2286	−0.0114	−0.3938	−0.0607	−0.2758	−0.2764	−0.1567
	(0.1155)	(0.1662)	(0.0831)	(0.1155)	(0.0901)	(0.1766)	(0.1098)	(0.1395)
social, religious services	−0.2746	−0.2076	−0.5244	−0.0735	−0.0875	−0.1564	−0.4385	−0.1093
	(0.1014)	(0.1244)	(0.1073)	(0.1132)	(0.1200)	(0.1000)	(0.1063)	(0.0854)
transportation, moving	−0.2817	−0.2446	−0.3017	−0.1060	−0.2616	−0.1731	−0.5332	−0.1810
	(0.0577)	(0.0932)	(0.0473)	(0.0995)	(0.0585)	(0.1233)	(0.0642)	(0.1349)
Industry								
Male mix vs. female mix	**0.0242**	**0.0139**	**0.0410**	**0.0034**	**0.0342**	**−0.0122**	**0.0695**	**−0.0167**
manufacturing vs. other	**0.0792**	**−0.0003**	**0.1022**	**−0.0106**	**0.0797**	**−0.0561**	**0.1552**	**−0.0323**
service vs. other	**−0.0990**	**−0.0067**	**−0.0938**	**0.0071**	**−0.0670**	**0.0646**	**−0.1161**	**0.0350**
communication	0.1343	−0.3643	0.1541	0.0212	0.1758	−0.0417	0.2153	−0.3541
	(0.0865)	(0.1610)	(0.0753)	(0.1167)	(0.0706)	(0.1566)	(0.0820)	(0.1629)
durable goods manufacturing	0.0312	−0.3536	0.1249	−0.0214	0.0873	−0.0368	0.1459	−0.1669

Table 2.D.1. Results of extended wage regressions (standard errors in parentheses) – continued

	1980		1989		1998		2010	
	own	partner	own	partner	own	partner	own	partner
	(0.0533)	(0.1481)	(0.0466)	(0.1070)	(0.0536)	(0.1475)	(0.0586)	(0.1434)
education	−0.1521	−0.3331	−0.1391	0.0560	−0.1003	0.0933	−0.2533	−0.0756
	(0.0798)	(0.1505)	(0.0738)	(0.1104)	(0.0787)	(0.1450)	(0.0918)	(0.1431)
finance, insurance	−0.0175	−0.3437	0.0369	−0.0275	0.2029	−0.0166	0.1254	−0.0721
	(0.0762)	(0.1466)	(0.0653)	(0.1040)	(0.0698)	(0.1418)	(0.0698)	(0.1379)
accommodation, food	−0.2309	−0.4672	0.0482	−0.0396	−0.3765	−0.0246	−0.1876	−0.1731
	(0.1352)	(0.1631)	(0.1165)	(0.1160)	(0.1240)	(0.1522)	(0.1464)	(0.1536)
medical services	−0.0535	−0.2732	−0.1113	−0.0544	0.0020	−0.0304	−0.0789	−0.0789
	(0.0893)	(0.1488)	(0.0765)	(0.1052)	(0.0794)	(0.1429)	(0.0832)	(0.1373)
non-durable goods manufacturing	0.0018	−0.3441	0.0285	−0.0034	0.0901	−0.0277	0.1231	−0.0402
	(0.0604)	(0.1473)	(0.0550)	(0.1103)	(0.0577)	(0.1493)	(0.0661)	(0.1597)
prof., scientific, manag. services	−0.0451	−0.4381	0.1193	−0.0467	0.1335	−0.0072	0.0543	−0.0899
	(0.0706)	(0.1509)	(0.0594)	(0.1072)	(0.0593)	(0.1431)	(0.0645)	(0.1394)
public administration	0.0690	−0.3987	0.0615	0.0810	−0.0488	0.1347	0.1313	−0.0697
	(0.0853)	(0.1580)	(0.0655)	(0.1152)	(0.0731)	(0.1498)	(0.0733)	(0.1477)
retail trade	−0.1699	−0.4487	−0.1087	−0.0149	−0.0856	−0.0003	−0.2484	−0.2127
	(0.0667)	(0.1495)	(0.0527)	(0.1046)	(0.0601)	(0.1409)	(0.0685)	(0.1439)
social assistance, arts, other	−0.2056	−0.2539	−0.1009	0.0289	−0.2644	0.0647	−0.1896	−0.0736
	(0.0702)	(0.1524)	(0.0664)	(0.1127)	(0.0651)	(0.1467)	(0.0781)	(0.1401)
transportation	0.0167	−0.2147	0.0206	0.0761	0.1131	−0.0335	0.1810	−0.0618
	(0.0648)	(0.1615)	(0.0616)	(0.1182)	(0.0624)	(0.1577)	(0.0745)	(0.1583)
utilities	0.1520	−0.5954	0.1214	0.0529	0.1395	−0.1797	0.0853	−0.3090
	(0.0865)	(0.2181)	(0.0672)	(0.1787)	(0.0819)	(0.1930)	(0.0833)	(0.1838)
wholesale trade	−0.1510	−0.5585	0.0241	−0.1321	0.0638	−0.0259	−0.1524	−0.2569
	(0.0781)	(0.1658)	(0.0623)	(0.1232)	(0.0703)	(0.1586)	(0.0725)	(0.1550)
Education								
Male mix vs. female mix	**0.0059**	**0.0008**	**0.0113**	**0.0045**	**−0.0050**	**0.0077**	**−0.0276**	**−0.0062**
yrs education	0.0324	0.0098	0.0237	0.0207	0.0420	−0.0501	0.0420	−0.0099
	(0.0076)	(0.0102)	(0.0089)	(0.0105)	(0.0121)	(0.0124)	(0.0127)	(0.0145)
bachelor (only)	0.1448	0.0327	0.1527	0.0576	0.0885	0.3276	0.2157	0.1369
	(0.0443)	(0.0519)	(0.0416)	(0.0444)	(0.0475)	(0.0481)	(0.0497)	(0.0525)
advanced degree	0.1109	0.0541	0.2410	0.1071	0.1888	0.3772	0.2479	0.1311
	(0.0706)	(0.0802)	(0.0630)	(0.0696)	(0.0740)	(0.0756)	(0.0759)	(0.0823)
Union & Government								
Male mix vs. female mix	**0.0195**	**0.0183**	**0.0148**	**0.0062**	**0.0001**	**0.0100**	**0.0076**	**0.0017**
union coverage	0.1289	0.1161	0.2054	0.0391	0.2066	0.1223	0.1321	0.0582
	(0.0299)	(0.0367)	(0.0280)	(0.0337)	(0.0319)	(0.0365)	(0.0384)	(0.0415)
work for government	−0.0129	−0.0323	−0.0033	−0.1193	0.0456	−0.1231	−0.1251	−0.0312
	(0.0421)	(0.0421)	(0.0375)	(0.0397)	(0.0456)	(0.0418)	(0.0455)	(0.0451)
Couple variables								
Male mix vs. female mix	**0.0082**		**0.0063**		**0.0032**		**0.0019**	
standard metropolitan statistical area	0.1622		0.0914		0.0620		0.0600	
	(0.0284)		(0.0225)		(0.0248)		(0.0273)	
Census region northeast	-0.0023		-0.0224		0.0292		0.0296	
	(0.0397)		(0.0342)		(0.0386)		(0.0408)	
Census region northcentral	0.0171		-0.0916		-0.0188		-0.1375	
	(0.0370)		(0.0334)		(0.0353)		(0.0394)	
Census region south	-0.0803		-0.1300		-0.0293		-0.0846	

Table 2.D.1. Results of extended wage regressions (standard errors in parentheses) – continued

	1980	1989	1998	2010
	own partner	own partner	own partner	own partner
	(0.0383)	(0.0344)	(0.0373)	(0.0400)
black	-0.1140	-0.0902	-0.1454	-0.1959
	(0.0444)	(0.0394)	(0.0459)	(0.0498)
hispanic	-0.1193	-0.0783	-0.0995	0.0898
	(0.0735)	(0.0591)	(0.1190)	(0.0615)
other non-white	0.0239	-0.1086	-0.0726	0.2530
	(0.1760)	(0.1210)	(0.0869)	(0.1142)
R^2	0.501	0.502	0.491	0.532
Num. obs.	902	1312	1288	1179

Notes: Each regression split into two columns to display coefficients on own and partner characteristic next to each other. Bold print: summary statistics. Normal print: estimated coefficients (standard errors). *High-pay professional* occupations: "architect", "artist", "computer, mathematics", "healthcare" excluding nurses, "lawyer, judge, physician", "legal assistant, teacher" excluding kindergarten, preschool, elementary, middle and high school teachers, "postsecondary teacher", "scientist", "social, religious services". *Manufacturing* sector: durable and non-durable goods manufacturing. *Service* sector: all industries except durable and non-durable manufacturing, utilities, mining, and construction industries. Omitted occupation: "manager", omitted industry: "mining and construction", omitted highest educational degree: "no degree", omitted region: "west", omitted race:"white". * In 1981, there are no dual-earner couples with a female partner working as lawyer, judge or physician. Results are robust to omitting all four couples with the male partner being a lawyer, judge, or physician in this year.

3 The Gender Wage Gap, Labor-Market Experience, and Family Choices: Lessons from East Germany

3.1 Introduction

Across the developed world, gender wage gaps persist since decades, serving as a stark reminder of the challenges that women continue to face in the labor market (Goldin 2014; Bertrand 2020). A pivotal element contributing to this disparity is the lower labor-market experience of women (Blau and Kahn 2017), often due to career interruptions and reductions in labor supply following child birth.[30] Supporting gender equality has become an important societal goal, and an essential stepping stone toward this goal is enabling mothers to maintain their professional careers, especially during the crucial early years of their children's lives (Cortés and Pan 2023). In this context, extending the public provision of affordable child care is usually viewed as a cornerstone ingredient of any policy strategy. Yet, there are also proposals to complement this with measures supporting the creation of family-friendly workplaces, which would allow mothers easier reconciliation of work and family (Goldin and Katz 2016), or encouraging child-care leaves by fathers, which would enable mothers to return to work sooner (Geyer, Haan, and Wrohlich 2015; Périvier and Verdugo 2024).[31]

[30]The link between (maternal) labor supply reductions and the gender wage gap has been emphasized in the literature, see Goldin (2006), Goldin (2014), Bertrand, Goldin, and Katz (2010), Angelov, Johansson, and Lindahl (2016), Kleven, Landais, and Søgaard (2019), Bertrand (2020), Kleven, Landais, and Søgaard (2021), Andresen and Nix (2022), and Cortés and Pan (2023).

[31]Goldin and Katz (2016) highlight the transformation of the pharmacist occupation into a family-friendly profession with significant time flexibility and no associated wage penalties. In Germany, child-care leaves by fathers were promoted in 2007 with the restructuring parental allowances to the so-called *Elterngeld* (Welteke and Wrohlich 2019). Now, if both parents take parental leave, they are eligible for 14 months of benefits instead of 12 months. *Elterngeld* replaced the means-tested *Erziehungsgeld* in Germany, which amounted to 300€ per month for a maximum of 24 months. See, e.g., Geyer, Haan, and Wrohlich (2015) for the effects of the reform and availability of subsidized child care on maternal employment. For Sweden, Ekberg, Eriksson, and Friebel (2013) find no effects of a daddy-moths reform on maternal employment and wages, similar to the results of Périvier and Verdugo (2024) for France.

In this chapter, I aim at shedding light on the merits of these measures by considering a particularly interesting case study: the striking regional differences between both women's accumulation of labor-market experience and the gender wage gap within Germany. On a national level, the gender wage gap in Germany is about 20 percent and thus comparable to the United States. Yet, in the Eastern region of the country, which formed a sovereign socialist state from the end of World War 2 until 1990, the gap is only about 6%. Women in East Germany also return to work sooner after child birth, work more often in full-time employment and thus accumulate more valuable labor-market experience (Hanel and Riphahn 2012; Keller and Kahle 2018; Müller and Wrohlich 2020). One well-known likely factor behind this is that, often attributed to its history, former East Germany has a higher supply of daycare facilities, especially for children below the age of three.[32] Interestingly, in Germany the federal states and municipalities are responsible for funding and organization of daycare facilities, leading to a large regional variation in availability and scope of daycare.[33] But are there other factors enabling women in that region to reconcile family and work better than their peers in the West? Are specific structures of the East German economy or more frequent career interruptions of fathers, i.e. differing family choices concerning fathers, part of the reasons? If so, this would lend support to policy proposals aimed at encouraging the creation of such workplaces and such behavior of fathers also elsewhere. Potentially, women's stronger labor-market attachment in East Germany could also be attributed to the lower marriage rate there which would make trying to learn from Eastern Germany less attractive for policymakers elsewhere, since they would not want to discourage marriage due to the correlation of single parenthood with higher risk of

[32]Attendance rates in public child care for children under the age of three are substantially higher in East Germany compared to West Germany (41% vs. 10% in 2007, 53% vs. 32% in 2022). Child care attendance rates from 2007 to 2022 by federal state are provided by the Federal Statistical Office (2022b, p. 107). Accessible child care has been argued to play a critical role in facilitating East German mothers' participation in the workforce, although results on the causal effect of policy reforms are mixed (Bick 2016; Müller and Wrohlich 2016; Zoch and Hondralis 2017; Müller and Wrohlich 2020).

[33]The federal government only sets the overarching policies for child care standards but is responsible for implementing and funding of maternity protection, parental leave (*Elternzeit*), and parental allowances (*Elterngeld*). Hence, there are only minor differences in family benefits across federal states. For example, Bavaria provides families with a monthly lump-sum transfer (*Familiengeld*) on top of the *Elterngeld* at the national level. Additionally, Bavaria grants a means-tested financial support for parental daycare fees (*Krippengeld*). Saxony offers a means-tested transfer to those parents who do not use external child care (*Landeserziehungsgeld*). However, the majority of family benefits are the responsibility of the national government and therefore very similar across Germany. On the contrary, daycare falls under the jurisdiction of the federal states and municipalities with large regional differences in extent and implementation.

poverty thereby potentially impacting children negatively (see, e.g., Harkness, Gregg, and Fernández-Salgado 2020).[34]

I analyze data from the German Socio-Economic Panel (SOEP) to approach these questions. In a preliminary analysis, I apply Oaxaca-Blinder decompositions to investigate the importance of labor-market experience for today's gender wage gap in Germany as well as for the gap in the gap between the country's Eastern and Western regions. While the results underline that accumulated work experience contributes substantially to the gender wage gap in Germany, they also reveal that experience gaps between men and women being smaller in the East contribute substantially to the wage gap being smaller there.

Given the importance of gender gaps in labor-market experience, I then investigate these differences more closely with a close eye on how they differ between East and West Germany and why. I do so using a life-cycle regression approach with different measures of accumulated experience, i.e., full-time experience, part-time experience, unemployment experience, and experience in the labor force on the left-hand side. On the right-hand side, my main focus is on the interaction between dummies for age and region, the coefficients on which show how the accumulation of experience differs between East and West Germany. Varying sets of controls allow me to investigate to what extent these differences can be attributed to regional differences in factors like the industry-occupation mix, marriage rates, or daycare supply. I run regressions separately for both, women and men, and further differentiate between parents and non-parents, between parents with different numbers of children, as well as between different cohorts. These distinctions enable me to assess the roles played by children, former institutions, norms, and fathers' engagement in care work.

Not surprisingly, experience gaps between women in East and West Germany are mainly driven by mothers and their differing labor-supply decisions over the life cycle. Specifically, East German mothers spend significantly more years in the labor force. Though slightly smaller, these differences persist also for younger cohorts, who spent their working lives in reunified Germany with the same laws and regulations. Interestingly, I find that the documented differences are hardly affected when controlling

[34]The tax and transfer system is often mentioned in the context of low female and maternal labor supply in Germany. Since the tax system is the same in reunified Germany, it is unlikely to influence different labor supply rates in East and West Germany directly.

for worker and job characteristics, including education, marital status, industry, and occupation. That means that Eastern German women's closer attachment to the labor market is neither the result of different education levels and fertility choices nor a consequence of them working in different types of jobs. This is different when I incorporate daycare supply into the analysis. First, I exploit regional differences in daycare supply for children below the age of three within East Germany and find that there is a clear positive connection to experience, i.e., mothers in East Germany are able to accumulate more experience in states with higher coverage. Second, I use this correlation to show that East-West experience differences are substantially smaller when I control for a hypothetical experience measure that captures the East-West differences in daycare supply. As a last exercise for mothers, I show that East-West differences are constant in the number of children, which can be rationed with the different daycare entry ages in East and West Germany. This underscores the decisive role of child care in understanding the rather gender-egalitarian labor market of East Germany and the different choices made in the family concerning mothers' labor force participation.

Strikingly, career interruptions by fathers seem not to play any role in Eastern German mothers being able to return to work more quickly after giving birth compared to mothers in West Germany. If East German fathers were indeed interrupting their careers (more) to allow their partners to resume theirs, we should observe East German men accumulate less experience compared to West German ones. While there is indeed an East-West gap in father's accumulated full-time experience, this is entirely explained by their stronger exposure to unemployment and not by different participation choices in the family concerning fathers. There are no East-West differences in men's accumulated labor-force experience and, when focusing on a younger cohort, East German men seem to supply even more labor over the life cycle. Thus, if there are men ready to interrupt working, they seem to live in West, rather than East Germany.

The East German case thus does not lend support to policies aimed at supporting the creation of family-friendly workplaces or encouraging child-care leaves by fathers.[35] If wanting to copy the more gender-egalitarian environment of East Germany, policy

[35] To be clear, I do not claim that these policies do not work. Their intended results are just not part of the environment that allow East German women to combine motherhood and career better than their peers in the West.

should concentrate on extending the public provision of daycare, where East Germany does still stand out.

The remainder of this chapter is structured as follows. Section 3.2 relates this chapter to the literature. Section 3.3 presents the data and the sample selection. Section 3.4 decomposes the gender wage gap, first, in all of Germany, and second, separately for East and West Germany. Additionally, I decompose the East-West gap in the gender wage gap into an explained and unexplained part. Section 3.5 examines the accumulation of labor-market experience over the life cycle, first for women, and then for men. Section 3.6 concludes.

3.2 Related Literature

This chapter is related to several strands of the literature. First, it is related to the large literature on the gender wage gap (see, e.g., Blau and Kahn 2017; Averkamp, Bredemeier, and Juessen 2024; Boll, Jahn, and Lagemann 2017; Piazzalunga 2018; Fuchs et al. 2021; Minkus and Busch-Heizmann 2020). Prominent studies show that actual labor-market experience is central to understanding the gender wage gap (see, e.g. Mincer and Polachek 1974; Olivetti 2006; Gayle and Golan 2012; Blau and Kahn 2017). I add to this literature by stressing the role of labor-market experience and by examining more deeply an environment where women accumulate unusually much labor-market experience.

Second, there is a broad literature that focuses on labor-market experience in the form of past labor supply decisions and its role for wages. In their cohort studies, Noonan, Corcoran, and Courant (2005) and Bertrand, Goldin, and Katz (2010) stress the importance of workforce interruptions and working part-time for wages. Both studies document that large parts of the widening earnings gap over time between men and women can be related to differences in work interruptions and differences in weekly working hours. Using the SOEP, Paul (2016) estimates the causal effect of working part-time on wages. She finds that working part-time in the past has a negative effect on current wages, although the effect is smaller than the wage effect of work interruptions. My results strengthen these findings. Related to experience gaps is the literature on the motherhood penalty and its differences in East and West Germany. Several recent studies document higher motherhood penalties for mothers living in West Germany than for mothers living in East Germany (Jessen 2022; Collischon, Eberl, and Reichelt 2020; Bönke et al. 2022). Presumably, this is due to East German mothers returning to work earlier after giving birth than mothers in West Germany. Though not explicitly for East and West Germany, Chhaochharia et al. (2021) establish a link between the motherhood penalty and daycare. They document lower motherhood penalties for German counties with higher daycare provisions. I contribute to their work by highlighting the role of career interruptions for the gender wage gap.

Third, I contribute to the literature focusing on the provision of public child care and maternal labor supply. There is a vast literature that documents differences in and positive effects of the expansion of public child care on the labor supply of mothers in Germany (Domeij and Klein 2013; Bick 2016; Zoch and Hondralis 2017; Müller and Wrohlich 2016). My analysis underlines the importance of daycare supply for the East-West difference in experience accumulation. Studies using quasi-experimental policy reforms to quantify causal effects of the expansion of public child care find mixed results for Germany (Müller and Wrohlich 2016; Bick 2016; see Müller and Wrohlich 2020 for a short review) but also for other countries such as Norway (Havnes and Mogstad 2011).

For example, Müller and Wrohlich (2020) underline that preferences for the quality of daycare can also dampen the response of maternal labor supply. Specifically, Schober and Spiess (2015) find a negative correlation between group sizes in daycare and maternal employment of mothers with children below the age of three in East Germany. Schober and Spiess (2015) point out that due to the lower availability of daycare for children under the age of three in West Germany, parents in West Germany could have more doubts with regard to the quality of daycare. Additionally, Bick (2016) stresses the role of nonpaid, nonmaternal child care for the inconclusive results. Similarly, Havnes and Mogstad (2011) find that, in Norway, the extension of public child care does not increase maternal labor supply but mostly crowds out informal child care arrangements. I contribute to this literature by ruling out more child care by fathers in East Germany compared to West Germany as a major channel. Closely related to my analysis focusing on fathers, Pollmann-Schult and Reynolds (2017) investigate the actual and preferred labor supply of fathers in West Germany. Their primary finding indicates that, in West Germany, fatherhood has a minimal impact on the hours fathers wish to work. I add to their work by showing that there is no substantial difference in the accumulated labor supply of fathers in East and in West Germany. In line with that, there is a recent study for France investigating child care provided by fathers. Using a policy reform, Périvier and Verdugo (2024) show that increasing the earmarked months of parental leave for fathers in France in 2015 did not lead to an increased participation of fathers.[36] Regarding the division of labor within couples, Bünning (2020) shows that fathers who work part-time contribute more to domestic work (in both housework and child care), but only during their part-time employment.[37] She relates parts of this result to a mix of time availability constraints, bargaining power, and gender ideologies. My study complements her work by investigating the labor-market attachment of fathers and mothers over the life cycle, also investigating differences in experience in part-time employment.

Fourth, the literature has emphasized differences in gender norms and attitudes toward female labor supply (see, e.g., Jessen, Schmitz, and Weinhardt 2024) and toward maternal labor supply (see, e.g., Welteke and Wrohlich 2019, Collischon, Eberl, and Reichelt 2020 or Boelmann, Raute, and Schönberg 2021) for understanding differences in women's employment patterns between East and West Germany (Müller and Wrohlich 2020). The male breadwinner norm has been prevalent in West Germany, whereas this is not the case in East Germany (Lippmann, Georgieff, and Senik 2020). East Germany has been shown to follow more gender-egalitarian norms in line with higher employment rates for women, and there has been a slow convergence in attitudes between East and West since reunification 30 years ago (Alesina and Fuchs-Schündeln 2007; Bauernschuster and Rainer 2012; Beblo and Görges 2018; Campa and Serafinelli 2019; Bondar and Fuchs-Schündeln 2023). For example, Campa and Serafinelli (2019) use a spatial regression discontinuity design at the former border to show that women in East Germany value the importance of work and career more than their West German counterparts.[38] Recently, the horizontal transmission of gender norms is the subject of

[36]On the contrary, the authors find a positive effect on father's earnings. The increase in the earmarked months of paternal leave of fathers simultaneously leads to shorter parental leave for mothers. The authors point out that the shorter parental leave for mothers could encourage fathers to work *more* instead of taking parental leave.

[37]Only fathers whose female partner works full-time, too, continue to provide more domestic work than before their part-time employment.

[38]Building a bridge between the expansion of public child care and gender ideologies, Zoch and Schober (2018) offer insights on the effects of the expansion of public child care on the attitudes of parents toward working mothers. However, their insights are somewhat inconclusive. They find a change toward less traditional gender ideologies for West German mothers in counties with low child care coverage. But for East German mothers, they find a change to more gender traditional gender

several studies exploiting migration between East Germany and West Germany. Main results are that East German mothers stick to their labor supply pattern despite West German surroundings (Collischon, Eberl, and Reichelt 2020; Jessen 2022; Boelmann, Raute, and Schönberg 2021). In addition, with sufficiently many East German peers arriving around, (native) West German women and mothers increase their labor supply in West Germany (Jessen 2022; Jessen, Schmitz, and Weinhardt 2024; Boelmann, Raute, and Schönberg 2021). Both findings indicate cultural diffusion, but only in the direction toward a more gender-egalitarian culture.[39] Related to preferences for conformity to peer behavior, Welteke and Wrohlich (2019) find causal peer effects on the decision of mothers regarding how long to take parental leave using a policy reform and employer-employee data for Germany. Interestingly, they find smaller reform and smaller peer effects in East Germany compared to West Germany. In line with the literature above, the authors explain this finding with smaller changes in social norms in East Germany. My overall results are in line with the positive attitudes and social norms toward working mothers in East Germany. Yet, in the existing literature, there is much less focus on what these more gender-egalitarian norms imply for the role of fathers in the household. I do not find fundamentally different labor-supply behavior of East and West German fathers, implying that any differences in norms rather apply to the perception of working mothers than that of non-working fathers. Further, my cohort analysis suggests that gender norms regarding work preferences have minimal, if any, relation to the persistent accumulation of East-West experience gaps.

In the broader context of OECD countries, Bertrand (2020) states that the main hurdles on the path to gender equality in the labor market are women's educational choices and their consequential decisions after becoming mothers. She stresses the importance of stereotypes about gender-specific skills and gender-specific roles as the drivers of the decision patterns of women. Using Germany as an interesting case with strong regional variation in both the raw gender wage gap, social norms, and maternal labor supply, I contribute to her findings by underlining that the observed massive experience gaps between women in East and West Germany are driven by mothers.

ideologies in response to an expansion of public child care. These results are possibly related to the education level.

[39] See Giuliano (2020) for a review on changes in gender norms toward, among others, female labor supply.

Exploiting the diverging labor supply choices of mothers, I provide insights about the importance of external child care and whether East German men or fathers contribute to the regional differences by behaving differently in their labor-market involvement compared to West German men.

3.3 Data

For the empirical analysis, I use the SOEP, a longitudinal survey run by the German Institute for Economic Research (DIW, Berlin).[40] The yearly survey was first implemented in 1984 in West Germany, and it covers both East and West Germany since 1990. Importantly, the SOEP provides information on labor-market experience, specifically, years of full-time, part-time, and unemployment experience. The DIW creates and provides the experience variables based on detailed monthly labor force status calendars in the individual questionnaires that allow to distinguish between full-time and part-time employment.[41] Respondents newly entering the SOEP are asked to report their labor force status in an annual calendar from the age of 16 up to the year of the survey. Even though also calendar reports suffer from retrospective bias (Jürges 2007), the question format using calendars in the SOEP can be expected to be more precise than the questions used in other surveys such as the Panel Study of Income Dynamics (PSID) where new respondents simply state the number of years they have worked full-time and part-time. The measure of labor-market experience in the SOEP has several advantages compared to the measures obtained in other survey data (if available at all), e.g., the PSID. First, the experience measures in the SOEP are available for all respondents, not only for subsamples (e.g., reference person and spouse). Second, because of the employment calendars used, the DIW can distinguish between full-time and part-time experience. This is particularly important for my analysis of employment histories in Section 3.5. Third, other than, e.g., the PSID which is only collected every other year, the SOEP is a yearly survey and therefore there are no issues with gap years.

Sample selection I use data for the period 1990 (first year where the SOEP includes respondents living in East Germany) to 2019 (last year before the COVID pandemic).

[40] Socio-Economic Panel (SOEP), version 36, 2021. For more details, see Goebel et al. (2019).

[41] In the questionnaire of the SOEP, full-time employment is defined as working 35 hours per week or more, working part-time is defined as working 20 to 34 hours per week.

I exclude self-employed or disabled individuals, pensioners, farmers or individuals in military service. Further, I drop individuals who are not living in the household of the respondent at the time of the survey. I also exclude individuals with missing experience information or whose reported experience implies that they have worked before the age of 15. I focus on respondents between 20 to 60 years old who are currently employed or who have worked in the past. I exclude individuals whose last reported occupation is in the military and individuals for which the SOEP reports a positive number of children over the life cycle but for which the children's years of birth are missing. Further, I exclude individuals who have missing data for the explanatory variables included in the analysis. The sample contains 145,861 person-year observations for men and 164,369 for women. For the different steps of my analysis, I use subsamples of this baseline sample.

Key variables and descriptive statistics Table 3.1 shows gender- and region-specific sample sizes and weighted averages for selected variables.[42] The SOEP provides the individual's region of residence during the survey year, based on the borders of the German Democratic Republic (East Germany) and the Federal Republic of Germany (West Germany) in 1990.[43] Columns (1) to (4) show the weighted means for women and men living in East and in West Germany. Columns (4) to (8) show the weighted means for parents, again by gender and region. Individuals are considered to be parents since the year of birth of their first child (biological or adopted).[44]

The first variable displayed in Table 3.1 is the real hourly wage used in the analysis of the gender wage gap in Section 3.4. The hourly wage rate is calculated as monthly labor earnings divided by monthly actual hours worked (see, e.g., Holst and Marquardt 2018; Selezneva and van Kerm 2016; Tyrowicz, van der Velde, and van Staveren 2018). I deflate wages to 2015 prices using the national Consumer Price Index (CPI).[45] Note

[42] I use standard individual weights throughout.

[43] For Berlin, East-West assignments are approximated by the DIW using zip codes.

[44] The birth year of the first child is provided by the SOEP. Information on children is asked in the biography interview at entry into the SOEP and updated during participation in the SOEP. Before 2001, men were not explicitly asked about their children's birth years and information about fatherhood is underestimated in the SOEP as only the context of the household is available to determine the respondent's biological children. Still, this should not be a problem for my comparison between East and West Germany, since any possible error is made for men in both regions (East and West) in the same way. The shares of men that are parents in survey years before 2001 are close to 50%, thereafter numbers are close to 60%.

[45] CPI data is obtained from the Federal Statistical Office (2022a).

Table 3.1. Descriptive statistics of selected variables.

	Women (n = 164,369)		Men (n = 145,861)		Mothers (n = 123,307)		Fathers (n = 90,913)	
	West (1)	East (2)	West (3)	East (4)	West (5)	East (6)	West (7)	East (8)
Number of observations	125,159	39,210	112,650	33,211	91,116	32,191	70,156	20,757
*Wages**								
Real hourly wage (in €)	14.6	11.7	18.6	12.6	14.7	12.2	20.1	13.7
Experience measures								
Years in labor force	16.0	18.7	19.1	19.5	17.8	21.0	22.3	22.1
Years of full-time experience	10.3	14.1	17.8	17.7	10.3	15.8	21.0	20.5
Years of part-time experience	5.0	3.2	0.7	0.6	6.7	3.6	0.6	0.5
Years in unemployment	0.6	1.4	0.7	1.2	0.8	1.5	0.6	1.0
Demographics								
Age	40.5	40.9	41.0	41.2	43.9	43.5	44.1	43.8
Age at birth of first child					25.4	23.2	29.1	26.5
Married	56.6	56.4	57.9	51.7	73.2	66.4	84.4	73.7
Number of kids	1.4	1.6	1.1	1.0	2.0	1.9	2.0	1.8
Years of education	12.1	12.5	12.2	12.3	11.7	12.5	12.1	12.5
Some tertiary degree (%)	23.0	32.4	28.7	28.7	19.7	33.7	31.3	32.5
Job characteristics (%)								
Working full-time	44.1	56.8	84.4	77.7	28.7	53.9	88.6	83.0
Industry (selected sectors)								
Agriculture	0.7	3.1	1.0	5.0	0.7	3.4	1.0	5.0
Manufacturing	17.6	12.9	36.9	26.2	18.0	12.8	39.7	25.6
Construction	1.6	2.4	9.8	16.8	1.9	2.5	10.2	17.6
Trade	21.3	19.3	11.2	11.3	22.2	18.1	10.0	9.4
Bank,Insurance	4.8	2.6	4.1	1.4	4.2	2.6	4.0	1.6
Services	49.0	52.9	27.1	27.0	48.4	53.7	24.9	28.8
Occupation by skill level								
Skill level: high	43.3	47.4	42.2	30.5	37.4	47.6	41.7	32.9
Skill level: medium	46.5	44.3	51.3	59.8	48.9	43.2	51.5	58.3
Skill level: low	10.2	8.3	6.4	9.7	13.7	9.2	6.7	8.8

Notes: Gender and region specific sample sizes and weighted averages for selected variables. Columns (1) to (4) show averages for all men and women, columns (5) to (8) show averages for individuals with children.
I follow the ISCO standards for the definitions of skill level by occupation group. See Appendix Table 3.B.1 for further variables. *Wages are only observed for currently employed individuals, not for all observations.

that wages are only available for currently employed individuals and hence not for the full sample.[46] Even for this very broad sample period, wage differences between men and women are substantially larger in West Germany (column (3) minus column (1), 4€) than in East Germany (column (4) minus column (2), 0.9€). I will analyze the gender wage gap in more detail in Section 3.4.

The key variables in my analysis are the experience measures provided in the SOEP, years of experience in full-time employment, in part-time employment, and in unem-

[46]Roughly 80% of the samples are currently employed, see Appendix Table 3.B.1. Men in West Germany have higher shares.

ployment.[47] In order to also compare total labor-supply histories, I add up those three measures to total years in the labor force. First, women (and even more so mothers) in West Germany (columns (1) and (5)) are the groups that accumulate, on average, the fewest years in labor force. Second, they are also the group that have the highest amount of part-time experience. For all experience measures except years in unemployment, differences between men and women are, again, substantially lager in West Germany than in East Germany. I investigate this pattern in more depth in the analysis of the gender wage gap in Section 3.4. Comparing only women (columns (1) and (2)), those in East Germany accumulate nearly four years more in full-time experience and approximately two years fewer in part-time experience. These differences are even more pronounced for mothers (columns (5) and (6)). Differences between East and West Germany for men and fathers are smaller (columns (3) to (4) and (7) to (8)). For both genders, individuals living in East Germany accumulate more time in unemployment. However, this aggregate comparison is only informative to a certain extent, since, e.g., age is not taken into account here.[48] Section 3.5 compares the accumulated experience differences between East and West Germany over the life cyle, and hence, for the same age groups.

The next group of variables in Table 3.1 contains demographic information. East and West German women have similar marriage rates at roughly 57%. In the sample of mothers, this share increases by almost 17% points in West Germany and only 10% points in East Germany. I define single motherhood as non-married motherhood. In East Germany roughly one third of mothers are not married, in West Germany it is only a quarter of mothers who are single mothers. For men and fathers, marriage rates are lower in East Germany, too. Further parents in East Germany are on average more than two years younger at the birth of their first child compared to parents in West Germany. On average, East German women have more children (1.6) than West German women (1.4). But conditional on having children, West German mothers have more children (2.0) than East German mothers (1.9).

Regarding years of education, in line with the literature, there is no gender education gap anymore and it is even reversed in East Germany. East German women have on

[47] For details on the data collection process for experience measures, please see the beginning of this Section 3.3.

[48] Note that the age average slightly differs between the samples.

average half a year of education more than women in West Germany. In East Germany, 32% of women have some tertiary education, compared to 23% in West Germany. Again, these differences are more pronounced in the sample of mothers. There are no differences for men/fathers in education variables between East and West Germany.

The last set of variables in Table 3.1 shows job characteristics. The share of men working full-time (80% or more) is substantially higher than the share of women working full-time (30% - 55%). This pattern is true in both East and West Germany but the gender differences are again considerably higher in West Germany. This is due to the remarkably lower full-time rates of West German women (44%), particularly mothers (less than 30%). Men (fathers) in East Germany have slightly lower full-time rates compared to men (fathers) in West Germany. In Section 3.5 I will offer a detailed analysis of East-West differences in (past) full-time employment over the life cycle. Next, I display selected groups of the last reported industry (eight one-digit groups, based on NACE).[49] Regarding the analysis of the gender wage gap in Section 3.4, note that there are substantial gender difference between industries. Men tend to work in manufacturing and construction sectors, women have higher shares in trade and service sectors. However, there are also notable regional differences relevant for the analysis in Section 3.5. The agricultural and construction sectors are larger in East Germany, whereas the share of individuals working in the manufacturing and banking sector is higher in West Germany. Even more striking are the East-West differences with regard to the last reported occupation (nine one-digit groups, ISCO-88 occupation code). Table 3.1 shows the sample shares in occupation groups aggregated by skill level.[50] Regarding women, women living in East Germany tend to work in occupations requiring higher skill levels compared to women living in West Germany. Again, this pattern is more pronounced in the sample of mothers. In contrast to that, the shares of men in East Germany are higher in occupations requiring *lower* skill levels compared to men in West Germany.

[49]NACE is the Statistical Classification of Economic Activities in the European Community. Due to low numbers of observations, I combine industry categories "Energy", "Mining", and "Other" into one category. See Appendix Table 3.B.1 for all eight industry groups.

[50]Appendix Table 3.B.1 provides the shares for all nine occupation groups.

3.4 Current gender and regional differences in wages and labor-market experience

In this section, I perform Oaxaca-Blinder wage-gap decompositions for Germany for 2019.[51] I will show that gender gaps in labor-market experience explain the largest parts in the gender wage gap. Then, I decompose the *East-West gap* in the gender wage gap into an explained and unexplained part. Also for understanding this "gap in the gap", labor-market experience will be shown to be critical.

3.4.1 Oaxaca-Blinder decomposition of the gender wage gap in Germany

Standard decomposition The first step of a standard Oaxaca-Blinder decomposition (Oaxaca 1973; Blinder 1973) is to estimate a log wage equation:

$$w_i = \beta_{g(i)} \cdot X_i + \epsilon_i, \tag{3.1}$$

where index g denotes gender (male, m, or female, f), $\beta_{g(i)}$ is a vector of coefficients, X_i is a vector of observable characteristics, and ϵ_i is a residual. Usually, the wage equation is estimated using data for men, $g = m$, because biases in the estimates for women are expected to be larger due to selection and potential labor-market discrimination.[52]

The gender wage gap is $\Delta = \overline{w}_m - \overline{w}_f$, where $\overline{w}_g$ is the average log wage by gender. Following the standard Oaxaca-Blinder decomposition, the gender wage gap can be decomposed into

$$\begin{aligned}
\Delta = \overline{w}_m - \overline{w}_f &= \widehat{\beta}_m \overline{X}_m + \underbrace{\overline{\widehat{\epsilon}}_m}_{=0} - \left(\widehat{\beta}_f \overline{X}_f + \underbrace{\overline{\widehat{\epsilon}}_f}_{=0} \right) \\
&= \widehat{\beta}_m \overline{X}_m - \widehat{\beta}_f \overline{X}_f \\
&= \widehat{\beta}_m \overline{X}_m - \widehat{\beta}_f \overline{X}_f + \widehat{\beta}_m \overline{X}_f - \widehat{\beta}_m \overline{X}_f
\end{aligned}$$

[51] Oaxaca-Blinder decompositions of the gender wage gap are usually done for a specific year, see, e.g., Blau and Kahn (2017) or Mischler (2021).

[52] The decomposition does not require the estimation of *both* wage equations. Kitagawa (1955) was the first to propose a decomposition of differences between two populations into an explained and unexplained part. Her decomposition approach can be seen as a special case of the Oaxaca-Blinder decomposition.

$$= \underbrace{\widehat{\beta}_m \underbrace{(\overline{X}_m - \overline{X}_f)}_{\substack{\text{Differences}\\ \text{in covariates}}}}_{\widehat{\Delta}|_X \text{ ("explained")}} + \underbrace{\overline{X}_f \underbrace{(\widehat{\beta}_m - \widehat{\beta}_f)}_{\substack{\text{Differences}\\ \text{in coefficients}}}}_{\widehat{\Delta}|_\beta \text{ ("unexplained")}} \tag{3.2}$$

where $\overline{X}_g$ denotes gender-specific average characteristics and $\widehat{\beta}$ indicates estimates. The decomposition yields an "explained" part of the gap,

$$\left(\widehat{\Delta}|_X\right) = \widehat{\beta}_m(\overline{X}_m - \overline{X}_f),$$

that is assigned to differences in observable characteristics and an "unexplained" part

$$\left(\widehat{\Delta}|_\beta\right) = (\widehat{\beta}_m - \widehat{\beta}_f)\overline{X}_f \tag{3.3}$$

that this approach identifies as unrelated to observable characteristics.

Averkamp, Bredemeier, and Juessen (2024) propose to additionally include the characteristics *of the partner* into the wage equation (3.1) to take into account career-prioritization within dual-earner couples ("extended decomposition").[53] I will provide results for both the standard and extended approach.

Specification of the wage equation For the Oaxaca-Blinder decomposition, I start from the standard specification of the wage equation in Blau and Kahn (2017) and extend it by variables used in the literature for the wage-gap decomposition in Germany (see e.g., Bauer and Sinning 2010 and Fuchs et al. 2021). I include the individual's education (years of schooling and dummy variables for bachelor and master degrees), labor-market experience (years of full-time experience, years of part-time experience), whether the individual has a migration background, a dummy for living in a rural area, as well as variables containing job information, such as industry, occupation, union coverage, and whether the respondent is working for the government. I include years of tenure as an additional experience measure. Years of tenure are defined as the number of years the individual has been with his current employer. Further, I include a dummy for living in East Germany. For other job information, I include a dummy for working full-time, whether the individual has a permanent contract, whether the individual is

[53] Using data for the U.S., they show that embedding the role of the family in the analysis of pay differences yields an unbiased decomposition.

Figure 3.1. Standard Oaxaca-Blinder decomposition of the gender wage gap in 2019.

Notes: Figure 3.1 shows the standard decomposition of the gender wage gap for Germany in 2019. The total of the colored areas corresponds to $\widehat{\Delta}|_X$, the gray colored area of the bar indicates $\widehat{\Delta}|_\beta$. Colors indicate variable groups, details are specified in the main text.

paid according to a collectively agreed wage agreement, whether the wage is imputed by the DIW, and the size of the firm in terms of the number of employees.

Results for Germany as a whole For the analysis of the gender wage gap in Germany, I focus on a subsample of employed men and women with positive wages in survey year 2019.[54] Figure 3.1 shows the decomposition of the gender wage gap in Germany in 2019, using the variables presented above. The total height of the bar shows the total gender wage gap in log points. In Germany as a whole, this gap is $\Delta = 19.1$ log points.[55]

The gray colored area of the bar indicates the part of the gender wage gap that cannot be explained by gender differences in observables, $\widehat{\Delta}|_\beta$. The total of the colored areas corresponds to the part of the gender wage gap that is explained by gender differences in covariates, $\widehat{\Delta}|_X$. The variable group "experience" (coral red) contains years of full-time and part-time experience, and years of tenure. The variable group "education"

[54]Following the treatment used in the official decomposition of the Federal Statistical Office (FSO), in my baseline analysis I also keep part-time employed individuals. Further, I focus only on individuals without missing values in explanatory variables, listed in the specification of the wage equation. I drop outliers with very low (below the 0.5% percentile) or very high (above the 99.5% percentile) wages separately for both genders. The sample for the gender wage gap analysis consists of 4416 men and 5214 women. Appendix Table 3.A.1 shows weighted means.

[55]This is in line with the official data on the gender wage gap for Germany provided by the FSO.

(gold) contains years of education and the variables related to the university degree. “Demographics” (green) collects migration background, living in East Germany, and living in a rural area. The variables industry (turquoise) and occupation (sky blue) are not summarized in groups because of the importance of gender segregation along these dimensions highlighted in the literature (see, e.g., Blau and Kahn 2017).[56] “Other job information” (purple) collects remaining job variables, working full-time, permanent contract, imputed wage, collective wage agreement, and firm size.

70% of the total gender wage gap can be related to gender differences in observables. Gender differences in measures of labor-market experience, indicated by the coral red area, are by far the largest contributing factor. 7.6 log points, or equivalently 40%, of the gender wage gap can be related to gender differences in experience. The second largest contribution, which is already substantially smaller, is associated with gender differences in industry shares, indicated by the turquoise-shaded area.

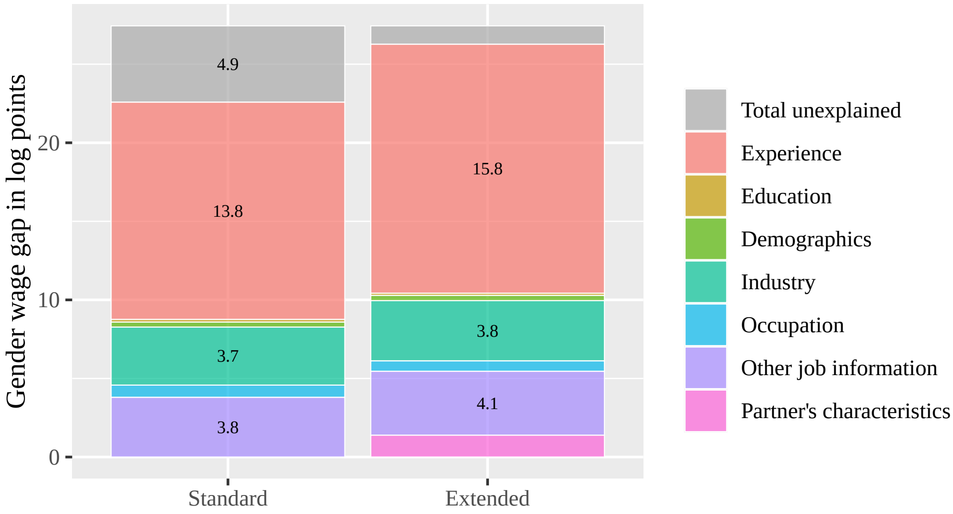
In Appendix Figure 3.A.1, I restrict the analysis to a sample of full-time employed individuals. In line with my baseline results, I find that the biggest share of the gender wage gap can be related to gender differences in labor-market experience.

As a robustness check, I also provide results using the extended decomposition developed by Averkamp, Bredemeier, and Juessen (2024). For this approach, one has to select on dual-earner households. For completeness, I first perform the *standard* decomposition using the dual-earner sample (left bar in Figure 3.2). The right bar in Figure 3.2 shows the results when additionally accounting for partner characteristics, following Averkamp, Bredemeier, and Juessen (2024). In line with the results for the U.S. reported by Averkamp, Bredemeier, and Juessen (2024), the extended approach explains larger shares of the gender wage gap (96%) than the standard approach (82%) (in the dual-earner sample).[57] In the dual-earner sample, results are even more pronounced regarding the role of gender experience gaps for the gender wage gap. Differences in labor-market experience explain 51% of the gender wage gap in the standard approach (left bar of Figure 3.2) and almost 60% of the gender wage gap in the extended specification (right bar of Figure 3.2). The contribution of experience to the wage gap is even

[56] Working for government is attributed to “Occupation”, following Blau and Kahn (2017).

[57] In the dual-earner sample, the gender wage gap is substantially larger (27.4 log points) compared to the main sample (19.1 log points). Apparently, both decomposition approaches explain higher shares in the dual-earner sample than the standard approach in the main sample in Figure 3.1.

Figure 3.2. Robustness checks using dual-earner sample, 2019.



Notes: Figure 3.2 shows the decomposition of the gender wage gap in the dual-earner sample in 2019. The left bar shows the standard approach, the right bar shows the extended approach following Averkamp, Bredemeier, and Juessen (2024). The total of the colored areas corresponds to $\widehat{\Delta}|_X$, the gray colored area of the bar indicates $\widehat{\Delta}|_\beta$. Colors indicate variable groups, details are specified in the main text.

larger than in the larger sample considered in Figure 3.1, roughly three fifths of the wage gap are attributed to differences in experience - far more than any other contributing factor.

3.4.2 Decomposing the "gap in the gap"

The analysis of the gender wage gap in Section 3.4.1 has underlined the importance of gender experience gaps for wage differences. As a next step, I investigate the "gap in the gap", i.e., the differences between East and West Germany regarding pay discrepancies between men and women. For this purpose, I show a decomposition of the East-West gap in the gender wage gap into an explained and unexplained part in an Oaxaca-Blinder decomposition style.

A decomposition of the East-West gap in the gender wage gap The gender wage gap in region R is $\Delta_R = \overline{w}_{m,R} - \overline{w}_{f,R}$, where $\overline{w}_{g,R}$ is the average log wage by gender (men,

m, or women, f) in region R (East Germany, E, West Germany, W). To begin with, the gender wage gap in region R can be decomposed as[58]

$$\begin{aligned}\Delta_R = \overline{w}_{m,R} - \overline{w}_{f,R} &= \widehat{\beta}_{m,R} \underbrace{(\overline{X}_{m,R} - \overline{X}_{f,R})}_{\substack{\text{Differences}\\ \text{in covariates, } \Theta_R^{\overline{X}}}} + \overline{X}_{f,R} \underbrace{(\widehat{\beta}_{m,R} - \widehat{\beta}_{f,R})}_{\substack{\text{Differences}\\ \text{in coefficients, } \Theta_R^{\widehat{\beta}}}} \\ &= \underbrace{\widehat{\beta}_{m,R}\Theta_R^{\overline{X}}}_{\widehat{\Delta}|_X \text{ ("explained")}} + \underbrace{\overline{X}_{f,R}\Theta_R^{\widehat{\beta}}}_{\widehat{\Delta}|_\beta \text{ ("unexplained")}} \end{aligned} \tag{3.4}$$

where $\overline{X}_{g,R}$ denotes gender-specific average characteristics in region R, and $\Theta_R^{\overline{X}} = \overline{X}_{m,R} - \overline{X}_{f,R}$ measures the gender gap in average characteristics in region R. $\Theta_W^{\widehat{\beta}}$ measures the gender gap in coefficients in region R.

Now denote the difference between the gender wage gap in West and East Germany (the "gap in the gap") as Γ,

$$\Gamma = \Delta_W - \Delta_E = \overline{w}_{m,W} - \overline{w}_{f,W} - (\overline{w}_{m,E} - \overline{w}_{f,E})\,. \tag{3.5}$$

With the expressions from equations (3.4) for East and West Germany, respectively, this can be written as

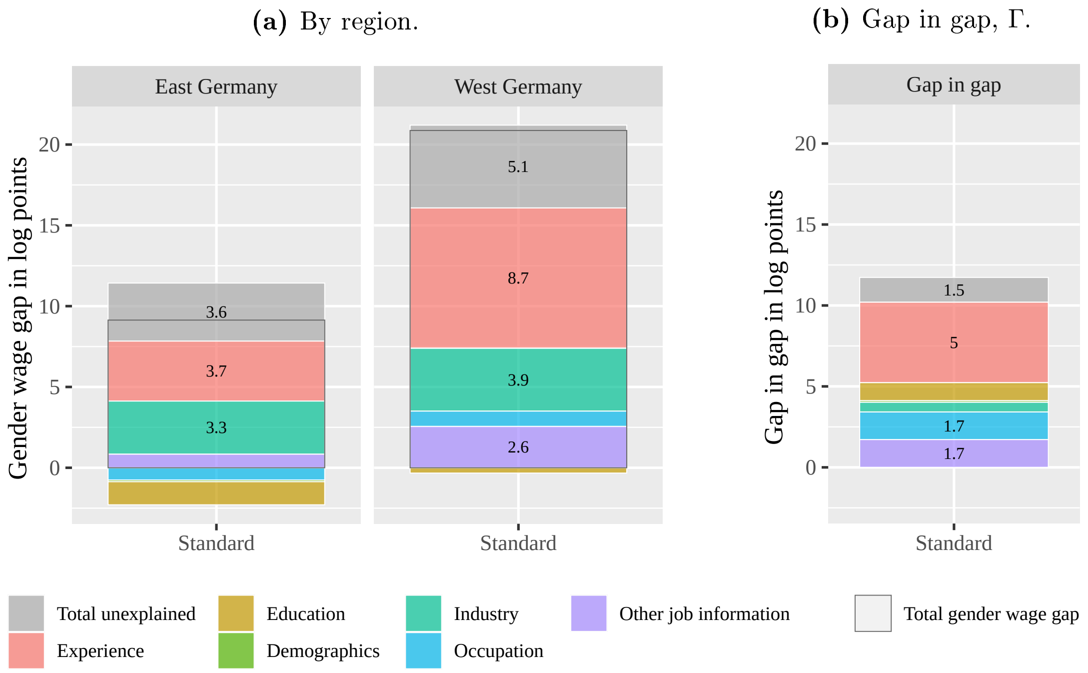
$$\Gamma = \Delta_W - \Delta_E = \widehat{\beta}_{m,W}\Theta_W^{\overline{X}} + \overline{X}_{f,W}\Theta_W^{\widehat{\beta}} - \left[\widehat{\beta}_{m,E}\Theta_E^{\overline{X}} + \overline{X}_{f,E}\Theta_E^{\widehat{\beta}}\right].$$

Extending by zero with $\widehat{\beta}_{m,W}\Theta_E^{\widehat{\beta}}$ and rearranging gives the decomposition of the decomposition:

$$\begin{aligned}\Gamma = \Delta_W - \Delta_E &= \widehat{\beta}_{m,W}\Theta_W^{\overline{X}} - \widehat{\beta}_{m,E}\Theta_E^{\overline{X}} + \overline{X}_{f,W}\Theta_W^{\widehat{\beta}} - \overline{X}_{f,E}\Theta_E^{\widehat{\beta}} \\ &\quad + \widehat{\beta}_{m,W}\Theta_E^{\overline{X}} - \widehat{\beta}_{m,W}\Theta_E^{\overline{X}} \\ &= \underbrace{\widehat{\beta}_{m,W}\left(\Theta_W^{\overline{X}} - \Theta_E^{\overline{X}}\right)}_{\widehat{\Gamma}|_X \text{ ("explained")}} + \underbrace{\Theta_E^{\overline{X}}\left(\widehat{\beta}_{m,W} - \widehat{\beta}_{m,E}\right)}_{\widehat{\Gamma}|_\beta \text{ ("unexplained")}} \\ &\quad + \underbrace{\overline{X}_{f,W}\Theta_W^{\widehat{\beta}}}_{\widehat{\Delta}|_\beta^W \text{ ("unexplained")}} - \underbrace{\overline{X}_{f,E}\Theta_E^{\widehat{\beta}}}_{\widehat{\Delta}|_\beta^E \text{ ("unexplained")}}\,. \end{aligned} \tag{3.6}$$

[58] This initial step corresponds to a standard wage gap decomposition *by region* R, thus, a standard Oaxaca-Blinder decomposition performed separately for West and East Germany, respectively.

Figure 3.3. Decomposition by region and of differences between regions in 2019.



Notes: Figure 3.3a shows the decomposition of the gender wage gap in East Germany (left panel) and West Germany (right panel) based on the West German male wage equation. Specifically, I plot $\widehat{\beta}_{m,W}\Theta_E^{\overline{X}}$ and $\widehat{\beta}_{m,W}\Theta_W^{\overline{X}}$, which are the two components of the explained part $\widehat{\Gamma}|_X$ in equation (3.6). The differences between both terms, and hence $\widehat{\Gamma}|_X$, is shown in Figure 3.3b.

The first term on the RHS of equation (3.6), $\widehat{\Gamma}|_X$, is the measure of interest. It measures the part of the East-West gap in the gender wage gap that is related to – or "explained" by – differences in gender *gaps* in observables. This term consists of the parts attributed to gender differences in observables in region-specific decompositions of the gender wage gap in East and West Germany, using the West German male wage equation. When discussing the results below, I will plot the explained gap in the gap, $\widehat{\Gamma}|_X$, along with its two components, the region-specific explained gaps $\widehat{\beta}_{m,W}\Theta_E^{\overline{X}}$ and $\widehat{\beta}_{m,W}\Theta_W^{\overline{X}}$.

The last three terms on the RHS are portions of the gap in the gap that are "unexplained", adopting the terminology of Blinder (1973) and Oaxaca (1973). The second term measures the part that is related to differences in male coefficients between East and West Germany. The last two terms on the RHS give the difference between the unexplained parts of the gender wage gaps for West and East Germany, respectively. By definition, they also contribute to the "unexplained" part of the gap in the gap.

Results Figure 3 shows the results. The total gender wage gap in East Germany (left panel in Figure 3.3a) amounts to 9.1 log points, which is graphically the sum of all white framed rectangles, or, aggregated, the dark gray framed rectangle in this panel. With 20.9 log points the total gender wage gap in West Germany (right panel in Figure 3.3a) is substantially larger. Roughly 60% (75%) of the gender wage gap in East (West) Germany can be related to differences in observables.[59] In East Germany, gender differences in experience contribute 3.7 log points and constitute again the largest contributing factor. In West Germany, gender experience gaps explain 8.7 log points of the gender wage gap. Only gender differences in industry shares, and for West Germany also "other job information", amount to sizable contributions in East Germany and West Germany. Again, gender experience gaps dominate the decomposition. This is especially the case for West Germany, where gender experience gaps are largest.

I now turn to the analysis of the "gap in the gap", i.e., I investigate the East-West gap in the gender wage gap, $\widehat{\Gamma}$, from equation (3.6), and its decomposition into an explained and unexplained part, see Figure 3.3b. As before, I divide the gap in the gap into colored rectangles that can be related now to East-West differences in gender gaps in observables ($\widehat{\Gamma}|_X$) and the remaining unexplained part in gray (the sum of $\widehat{\Gamma}|_\beta$, $\widehat{\Delta}|_\beta^W$, and $\widehat{\Delta}|_\beta^E$). The bars can be interpreted analogously as before, only the variable groups now represent the contribution of *East-West differences* in gender differences in, for example, years of labor-market experience, to the gap in the gap.

The total East-West gap in the gender wage gap amounts to 11.7 log points. The major share (87%) of this gap in the gap can be related to East-West differences in gender differences in observables (again in coral red). East-West differences in gender gaps in experience are the major factor (42%) in explaining the gap in the gap. The other two sizable variable groups, both explaining 15%, are occupation shares (in sky blue) and other job information (in purple).[60] Although other factors also contribute to the gender wage gap, East-West differences in gender experience gaps dominate. This

[59] This includes the variable groups with negative contributions.

[60] This is in line with the study of Fuchs et al. (2021) who investigate the gender wage gap in NUTS 3 regions with IAB data. Their results indicate the importance of regional variation in firm size, occupation, tenure and, as their proxy for experience, age. This matches my results with respect to East-West differences, where East-West differences in experience gaps (years of labor-market experience and tenure), firm size ("other job information"), and occupation explain large shares of the gap in the gap.

pattern is even more pronounced in a sample of full-time employed workers, see Figure 3.A.2 in the Appendix.

Having shown that East-West differences in gender experience gaps explain almost half of the East-West gap in the gender wage gap, I now take a closer look at the accumulation of such gaps over the life cycle.

3.5 East-West differences in experience accumulation

Women in West Germany accumulate substantially less labor-market experience than women in East Germany, see Section 3.3. Apparently, this difference results from differences in accumulated labor-supply decisions of women regarding full-time employment, part-time employment and labor-market participation between the East and the West. I now investigate what drives regional differences in gender experience gaps.

3.5.1 Life-cycle regression approach

I measure differences between East and West Germany in the accumulation of labor-market experience over the life cycle using the following regression, estimated separately by gender g

$$y_{it} = \alpha_{gy}\, age_{it} + \beta_{gy} age_{it} \times east_{it} + \gamma_{gy} X_{it} + \delta_{gyt} + \varepsilon_{it} \tag{3.7}$$

where y_{it} is a measure for years of labor-market experience of individual i in year t, age_{it} is a full set of age dummies, $east_{it}$ is a dummy for living in East Germany[61] , X_{it} is a vector of additional explanatory variables to be discussed below, and δ_{gyt} are year effects. As I include a full set of age dummies, both linearly and in the interaction with the *east* dummy, the right-hand side includes neither a constant nor the non-interacted *east* dummy. I chose this specification rather than omitting one age category as it facilitates the interpretation of the coefficients.

Specifically, the coefficients α_{gy} give the average years of labor-market experience that an individual living in West Germany accumulates at his or her specific age. The

[61] Mobility rates in Germany are low (Stawarz et al. 2020). During the sample period, there is net migration from East to West Germany (Fuchs-Schündeln and Schündeln 2009; Stawarz et al. 2020), hence from the region where the experience gap is small to the region where it is larger. If there is a selection issue, it should lower the experience gap in West Germany and thereby cushion my results.

coefficients on the interaction term, β_{gy}, are the main coefficients of interest and give the average additional years of experience of an individual at a certain age living in East Germany compared to an individual of the same age living in West Germany. Without a separate East dummy in addition to the interaction term, the coefficients β_{gy} give the additional experience (conditional on observables in X) accumulated by an East German compared to a West German of the same age.

I use different measures of labor-market experience as dependent variable. The SOEP provides three measures directly, years of full-time experience, years of part-time experience, and years in unemployment. Because I am also interested in total labor-supply histories, I additionally combine those three measures to total years in the labor force. I estimate equation (3.7) as baseline specification without additional control variables, and with sets of additional explanatory variables described below. Section 3.3 discusses descriptive statistics on the key variables included in the analysis.

3.5.2 Estimation results for women

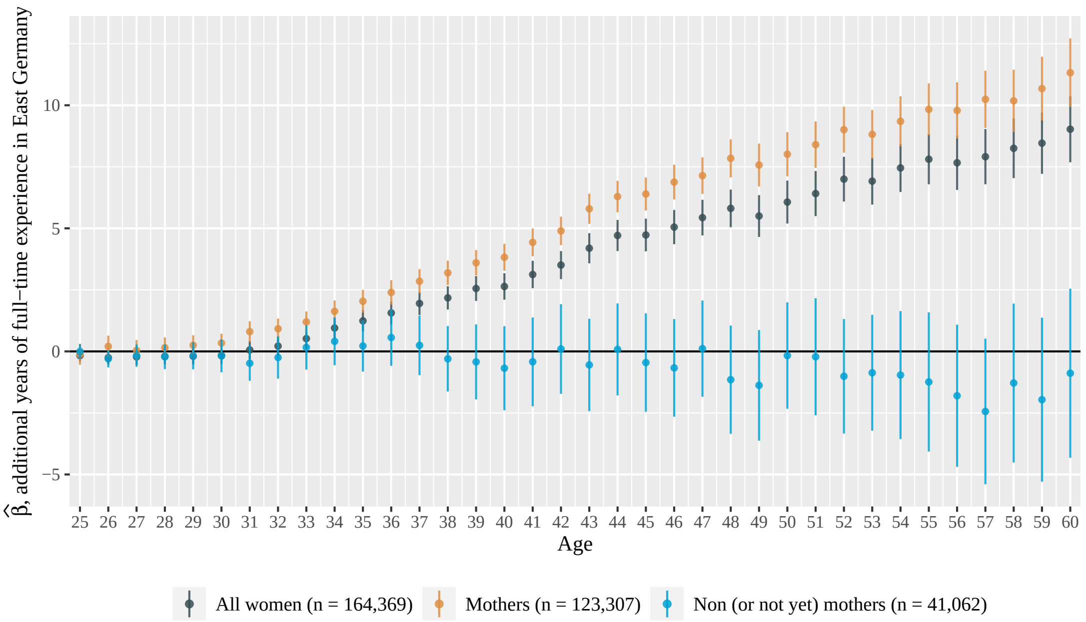
I first present estimation results for women.

Full-time experience Figure 3.1 shows the life-cycle pattern of the extra full-time experience accumulated by different samples of women in East Germany compared to those in the West (the estimated coefficients $\widehat{\beta}_{gy}$) along with 95% confidence intervals.[62] I consider three samples: All women (dark blue), women who have children (mothers, gold), and women who do not (yet) have children (sky blue).[63] Before age 33, there is almost no difference in the accumulation of full-time experience between East German and West German women in any of the different samples. After the age of 33, there emerge significant and quantitatively important differences between East and West Germany for all women (dark blue) and for mothers (gold). East German women (dark blue) accumulate substantially more full-time experience than West German women. This difference increases with age to up to more than nine years at age 60. For moth-

[62] I display the age range from 25 to 60 instead of 20 to 60 because education can be expected to be completed by the age of 25. Complete regression tables are displayed in Appendix Table 3.B.2.

[63] As pointed out by the literature, children are one of the remaining pain points toward greater gender equality (Bertrand 2020). Individuals are considered to be parents since the year of birth of their first child (biological or adopted). Women who will give birth at later ages are counted as not (yet) mothers.

Figure 3.1. Years of full-time experience, all women, mothers and non-mothers.



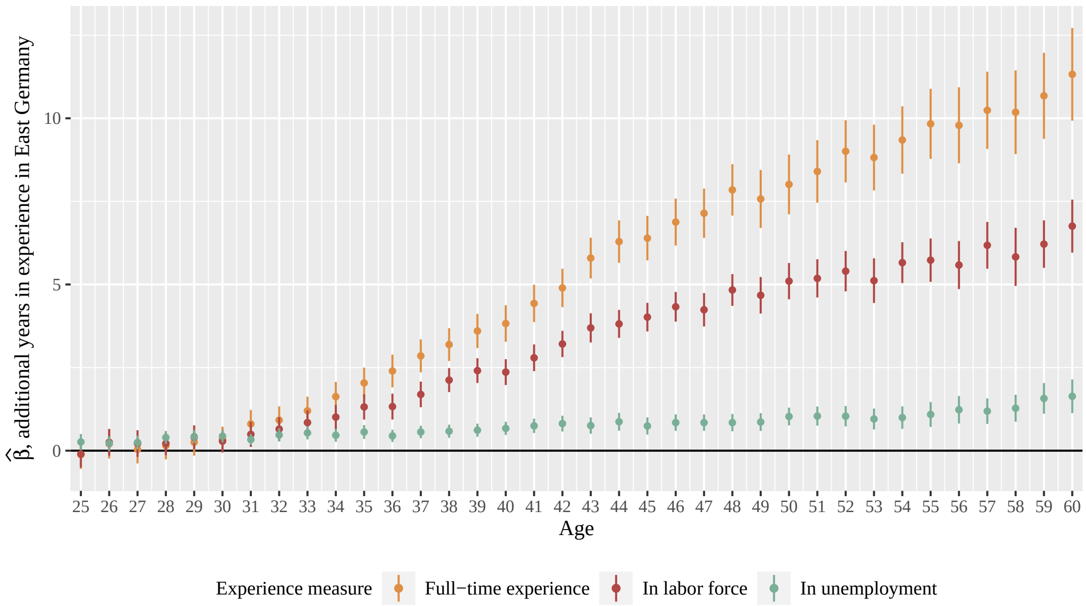
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using full-time experience as dependent variable. Standard errors are heteroscedasticity robust. I consider three samples: All women (dark blue), women who have children (gold), and women who do not (yet) have children (sky blue).

ers (gold), differences in full-time experience diverge more strongly between East and West Germany, resulting in a difference of eleven years at the age of 60. Differences in experience accumulate over the life cycle and there is no stagnation pattern, so that there results a persistent difference in employment patterns. Many mothers in West Germany do not return to full-time employment for a number of years and the ongoing accumulation over the life cycle implies that some never do.

A different picture emerges for the sample of women who do not (yet) have children (sky blue in Figure 3.1). For childless women, no significant differences between East and West Germany arise at any point over the life cycle.[64] These results show that the overall differences in full-time experience are driven by the different labor-supply decisions of *mothers* in East and West Germany. In the following, I will therefore focus on the sample of mothers. Results for the samples of all women or non-mothers are available in Appendix 3.B.

[64]For older women, the confidence intervals are larger due to the small number of observations. If anything, West German women without children accumulate slightly *more* years of full-time experience.

Figure 3.2. Years of full-time experience, years in labor force and years in unemployment, mothers.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using full-time experience (gold), years in labor force (deep red) or years in unemployment (sage green) as dependent variable. Standard errors are heteroscedasticity robust. The sample contains only mothers (n = 123,307).

Total years in labor force In West Germany, the share of women working in full-time employment is lower than in East Germany, see, e.g., Table 3.1. In contrast, unemployment is higher in East Germany. Hence, East-West differences in accumulated full-time experience might be driven by factors other than voluntary decisions by mothers not to work. I therefore additionally use total years in the labor force and years in unemployment as dependent variables to account for experience in part-time employment and unemployment.

Figure 3.2 shows the results for mothers with regard to the different experience measures.[65] For comparison, I repeat the estimation results for full-time experience of mothers (gold) from Figure 3.1. For experience in the labor force (deep red), differences

[65]Experience in full-time employment (gold), part-time employment (not displayed), and in unemployment (sage green) add up to experience in the labor force (deep red). For completeness, Appendix Figure 3.B.2 shows differences in years in the labor force for all samples of women. Appendix Figure 3.B.4 shows differences in the years of part-time experience over the life cycle. West German mothers accumulate significantly more years of part-time experience than their East German counterparts. East-West differences for non-mothers are insignificant. Appendix Figure 3.B.5 shows differences in years of unemployment. Women in East Germany accumulate 1.5 more years in unemployment, same as mothers. East-West differences for non-mothers are even higher.

between East and West German mothers at the same age are smaller than for full-time experience (gold). Yet, the differences still accumulate to sizable gaps of five years at the age of 50 and almost seven years at the age of 60. Similar to full-time experience, differences start becoming significant from the mid-thirties of mothers. For experience in unemployment (sage green), mothers in East Germany accumulate up to 1.5 more years in unemployment.[66]

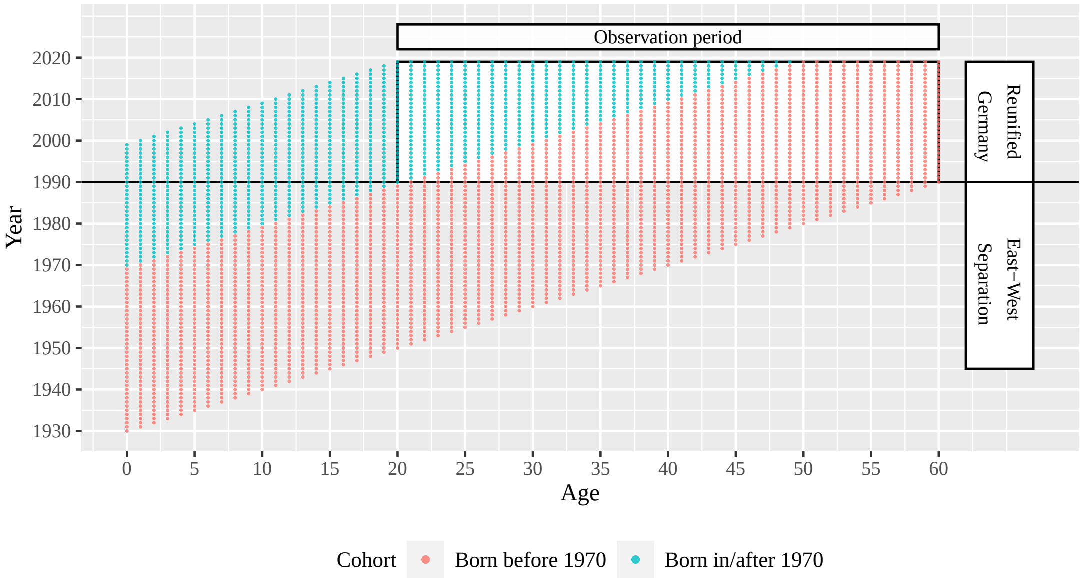
Overall, I find substantial experience differences for years in labor force, too. To look at full-time experience alone may be too strict with regard to West Germany because of higher part-time employment there. In what follows, I will focus on experience in labor force.

Sample split by cohort As discussed in the introduction, one appealing property of comparisons between East and West Germany is that the two regions share the same legal and regulatory framework. Yet, this is only true since the country was reunified in October 1990. Some women in my sample have accumulated labor-market experience or failed to do so before that date. In other words, some of the results discussed so far may reflect decisions taken before women in East and West Germany were subject to the same laws and regulations. It is important to make sure that the results are non solely driven by these decisions. For this reason, I now distinguish two cohorts of women, those born before and those born in or after 1970.[67] Figure 3.3 illustrates the age ranges of the two cohorts over time, with the horizontal line marking the reunification in 1990. The white rectangle highlights the available survey years in the SOEP together with the age range set for the analysis. Mothers born in or after 1970 (in turquoise) have worked most of their lives in reunified Germany and are very likely to have become mothers only after the reunification of Germany when they were 20 years old or younger. Thus, East and West German mothers in the younger cohort share the same laws and regulations with regard to, e.g., labor protection during motherhood, parental leave, parental allowances, and the tax system. Also, the younger cohort has not used public

[66]For completeness, I also consider a sample of currently employed women, which yields a sample that is more similar to the one used for the analysis of the gender wage gap in Section 3.4. By focusing on currently employed mothers, I rule out that the large experience gaps are driven by (probably West German) mothers who do not return to the labor market at all. Results for years in the labor force are similar for currently employed mothers, see Appendix Figure 3.B.1.

[67]Also Zoch (2021) starts her cohort analysis on changes in gender attitudes in East and West Germany with the cohort born in the 1970s.

Figure 3.3. Ages ranges of cohorts over time (conceptual).



Note: Conceptual overview of different policy regimes and age ranges of the cohorts in Germany before and during the observation period. The cohort born before 1970 is displayed in coral red, the cohort born in or after 1970 is displayed in turquoise. Following a depiction by Zoch (2021, Figure 1).

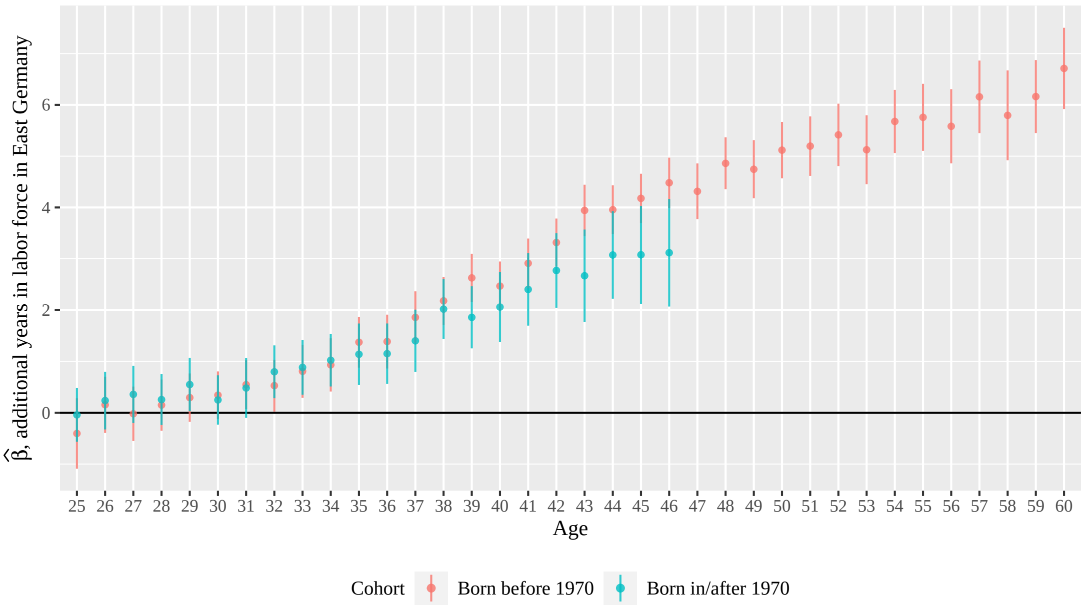
child care provided by former East Germany, but only child care provided in reunified Germany.[68] The majority of mothers in the older subsample, born before 1970 (coral red), have given birth before the reunification of Germany, with different institutional settings in East and West Germany.

Figure 3.4 shows the results for years in the labor force, split by year of birth (born before 1970 in coral red and born in or after 1970 in turquoise). Again, I focus on the results for mothers.[69] For both cohorts, significant differences between East and West German mothers arise in their mid-thirties. For the younger cohort, differences amount to 3 years at the age of 46. Overall, the analysis for the younger cohort yields quite similar patterns as for the older cohort. In the age range that can be compared for both cohorts, there are somewhat smaller differences in the younger cohort, but the differences between East and West remain quantitatively considerable. Appendix 3.B.2 provides

[68] During the 1990s, public child care coverage for children under the age of 3 was substantially higher in East Germany (36% in 1998) than in West Germany (3% in 1998). For comparison, before reunification, the child care coverage for children under the age of 3 was 56% in 1989 in East Germany (Dittrich, Peucker, and Schneider 2002, p. 100).

[69] Since the last survey year is 2019, I include individuals up to the age of 46 from the younger cohort. The oldest age groups in the younger cohort from age 47 to 49 only have a few observations and are therefore not included. Figure 3.B.2 in the Appendix shows the results for the different subsamples of women (all, mothers, and non-mothers).

Figure 3.4. Years in labor force, mothers by birth cohort.

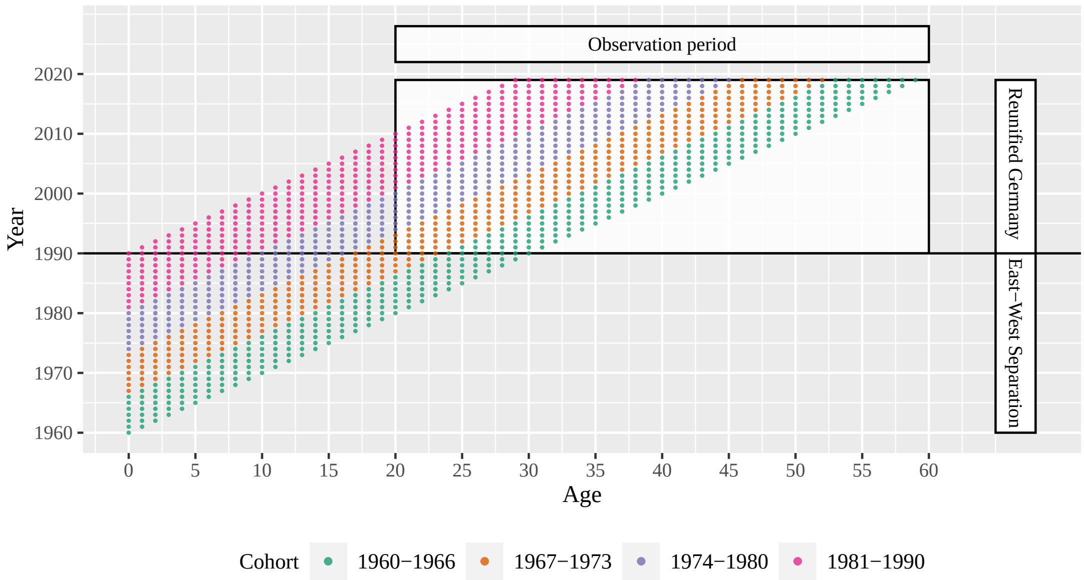


Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. Mothers born before 1970 (n = 84,203) are displayed in coral red, mothers born in or after 1970 (n = 37,726) are displayed in turquoise.

additional results for the pre/post-1970s cohort sample split that overall convey the same pattern. This reveals that the East-West differences in experience accumulation are not solely driven by labor-market choices taken before the reunification, but that East German women continued to have a stronger attachment to the labor force even when they were subject to the same laws and regulations as West German women after reunification.

Alternative cohort split Next, I investigate whether the previous result, that East German women continue to have a stronger labor market attachment, persists in a finer cohort split. I define four different birth cohorts, in a way that distinguishes cohorts in terms of exposure to the socialist regime in East Germany over their life cycle. I then compare my results to the cohort analysis in the related studies on gender norms by Beblo and Görges (2018) and Lippmann, Georgieff, and Senik (2020), who find different East-West gaps (in gender gaps) in work preferences for different cohorts. I closely follow Beblo and Görges (2018) in their definition of cohorts. Similar to the analysis above, I focus on cohorts that either did not work under the socialist regime at all or

Figure 3.5. Ages ranges of alternative cohorts over time (conceptual).



Note: Conceptual overview of different policy regimes and age ranges of the cohorts in Germany before and during the observation period. The color indicates the cohort. Following a depiction by Zoch (2021, Figure 1).

that spent most of their working life in reunified Germany, again to exclude that decisions during separation drive my results. Figure 3.5 illustrates the age ranges of the considered alternative cohorts over time. The first cohort (emerald green) considered here was born between 1960 and 1966 and aged 24–30 at the reunification (see Beblo and Görges 2018).[70] The first cohort spent their childhood, teenage years and first years in the labor force under the two different regimes, but after 1990 they have worked and lived in reunified Germany under the same laws and institutions. The second cohort, born between 1967 and 1973 (orange rust), was between 17 and 23 years old during the reunification, which means that they spent childhood and adolescence under the East-West separation. If at all, they have accumulated only very few years in the labor force under the two different regimes. For the third cohort (violet, born between 1974 and 1980) any labor force participation during the separation can be excluded since they were 16 years or younger at the time of the reunification. Hence, they spent their com-

[70]I display this rather "old" cohort for comparability of my results to Beblo and Görges (2018) and Lippmann, Georgieff, and Senik (2020), although, as argued above, these women are likely to have made decisive family and work decisions (shortly) before reunification. However, I do not include the even older cohorts considered in both studies. Both studies already find cohort differences for the cohorts considered in my analysis.

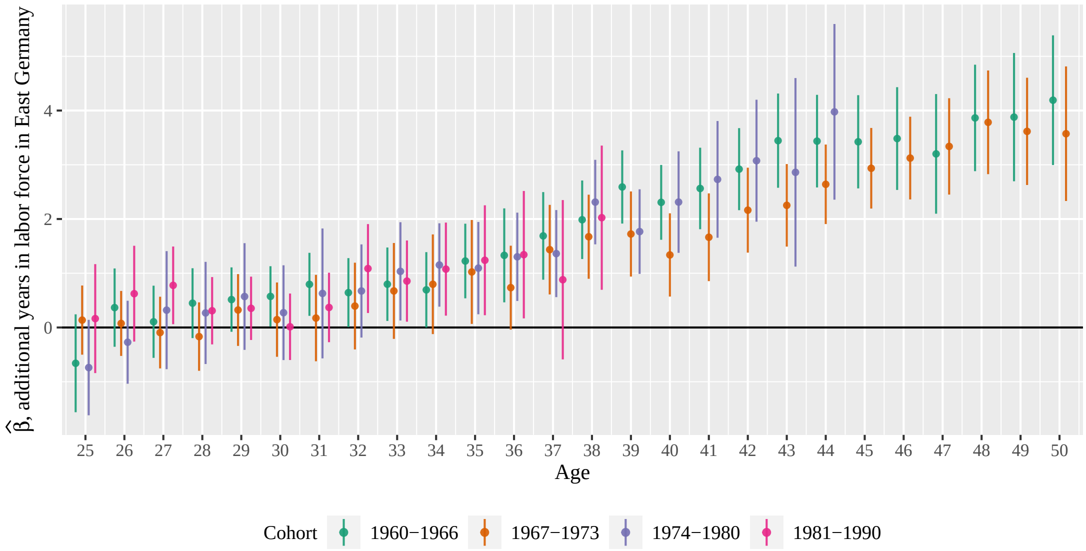
plete working life under the same laws and regulations in East and West Germany. As a last cohort, I consider individuals born between 1981 and 1990 (pink).[71] This youngest cohort only spent their (early) childhood under separation (aged 0 to 9 at reunification). Adolescence, higher education and employment all have taken place in reunified Germany. At least for the two youngest cohorts (violet and pink), I can exclude that their labor-supply histories are influenced by socialist policies, laws or regulations directly. This is less clear for the first two cohorts (emerald green and orange rust) since their exposure to the two regimes is substantially longer and present during adolescence and early adult life. Still, since the major part of their working lives has taken place *after* the reunification, so also for them most working decisions are made under the same laws and regulations. Further, the second, third, and fourth cohorts (orange rust, violet, and pink) all predominantly become mothers in reunified Germany, but they lived under the socialist regime for different lengths of time. Hence, this cohort split is an alternative way to show that the observed experience gaps are not driven by (family) decisions made during separation. At the same time, the cohort split exploits different exposure lengths to the socialist regime before reunification. If the observed cohort differences in gender norms (attributed to exposure to institutions during childhood by the literature) matter for labor supply decisions after reunification, I should find cohort differences in the East-West experience gaps.

Figure 3.6 shows the results for the alternative birth cohorts for years in labor force, cohorts are indicated by the same color as in Figure 3.5.[72] First, across all cohorts, significant East-West differences arise and accumulate over the life cycle. This supports the finding in Figure 3.4 that the East-West differences between mothers arise under the *same* institutions after reunification. Second, the accumulation of experience gaps evolves similarly across cohorts. Significant gaps arise during their mid-thirties and increase thereafter in similar magnitudes. Hence, different exposure lengths to the socialist regime during one's youth appear to have no substantial impact on the working decision in reunified Germany, at least for individuals born in 1960 or after. This is further support for my previous cohort split by 1970 and suggests that, for the

[71] This cohort is not specified by Beblo and Görges (2018) or Lippmann, Georgieff, and Senik (2020).

[72] The sample sizes and colors for the alternative cohorts of mothers are as follows: 1960-1966 in emerald green (n = 29,929), 1967-1973 in orange rust (25,647), 1974-1980 in violet (16,260), and 1981-1990 in pink (8147).

Figure 3.6. Years in labor force, mothers by alternative cohorts.



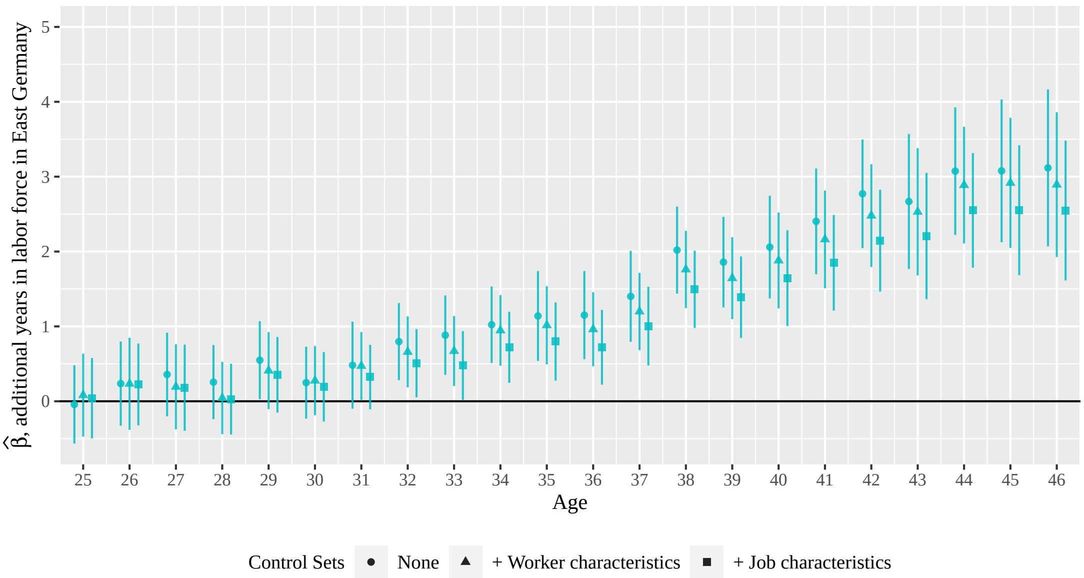
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. The color indicates the cohort, see the main text for sample sizes.

following evaluations, it is sufficiently detailed to focus on mothers born in or after 1970. Both Beblo and Görges (2018) and Lippmann, Georgieff, and Senik (2020) find different East-West gaps (in gender gaps) in work preferences between cohorts. I do not find such experience differences between cohorts with longer or shorter exposure. This speaks against East-West differences in gender norms such as work preferences being a prime factor for the prevailing experience differences between mothers in East and West Germany.

However, there are likely other factors driving the persistent gaps across cohorts, such as East-West differences in the industry mix and daycare coverage (investigated next) or in career interruptions of fathers (Subsection 3.5.3).

Worker and job characteristics I now turn to examine how differences between East and West in observable characteristics, such as education, number of children or the industry mix contribute to the differences in the accumulation of experience. Therefore, I investigate whether the documented differences between mothers shrink or even disappear once the effects of appropriate control variables have been accounted for.

Figure 3.7. Years in labor force with controls, mothers of young birth cohort.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Different sets of controls are indicated by point shape. Standard errors are heteroscedasticity robust. The sample contains only mothers born in or after 1970 (n = 37,726, in turquoise).

The results for mothers of the younger cohort are summarized in Figure 3.7. Note that the scaling in this figure is different from those shown before since this evaluation cannot include individuals in their 50s which is the age range where accumulated differences in labor-market experience are most pronounced, but the considered cohort has not yet reached sufficient numbers. For comparison, I repeat the estimates from the model without controls (point shape). The first set of controls contains worker characteristics (triangle shape). I include marital status, whether the individual was ever married, the number of children over the life cycle (as dummies), years of education and whether the individual has some tertiary degree.[73]

As described in Section 3.3, East German women, and especially mothers, have both more years in education and higher shares in tertiary degrees compared to West German women. At the same time, they are younger than women in West Germany when they start a family. Further, marriage rates in East Germany are lower than in the West and single and/or earlier motherhood could necessitate labor force participation to generate

[73]Detailed information on tertiary education as used in Section 3.4 is available only from 2010 onward.

some earnings and secure career paths. The results for this specification are plotted in triangles. I find that including worker characteristics leaves the coefficients on the interaction terms mainly unchanged. Hence, that mothers in the East return to work more frequently and more quickly cannot be attributed to differences in factors such as education levels, marriage, earlier childbirth, or any other personal characteristics. This is also true for the other experience measures and samples of women, compare Appendix Figures 3.B.2, 3.B.3, 3.B.4, and 3.B.5 in the Appendix.

As a second specification using control variables, I additionally include job characteristics (square shape in Figure 3.7). Here, I add to the previous model the last reported occupation, the last reported industry, and a dummy for currently working full-time.[74] The preliminary analysis in Section 3.3 has highlighted substantially higher full-time employment for East German mothers. Further mothers in the East work less often in the manufacturing and banking sectors but more often in the service sector than their West German counterparts. In addition to that, mothers in the East are more likely to work in occupations requiring higher skill levels. That might be a reason for the differences in experience accumulation between regions as returning to work after an interruption while having young children might be easier in some industries (such as the services sector) or more appealing in occupations demanding higher skill levels than in others. The estimates are plotted in squares. Including job characteristics slightly reduces East-West differences in years in labor force for mothers. But the difference between East and West German mothers still amounts to more than 2.5 years during their mid-forties, where the differences is three years without controls.[75] Hence, the East's industry-occupation mix is not responsible for mothers there wanting to work more.

Day care I now address how the higher degree of daycare availability in East Germany contributes to the stronger accumulation of labor-market experience of women in this region. That there is an effect of daycare on maternal labor supply is firmly established in the literature (see, e.g., Bauernschuster and Schlotter 2015; Bick 2016; Zoch and

[74] I use information on the last reported industry and occupation in order to avoid a selection on currently employed individuals.

[75] The reduction in point estimates is slightly stronger for full-time experience, see Appendix Figure 3.B.3. For the older cohort, including job characteristics reduces East-West differences considerably, coral red in Figure 3.B.3. However, this impact disappears when labor-force experience is considered, see Figure 3.B.2.

Hondralis 2017; Müller and Wrohlich 2020) and I aim at quantifying its role for the East-West gap in accumulated labor-market experience of women.

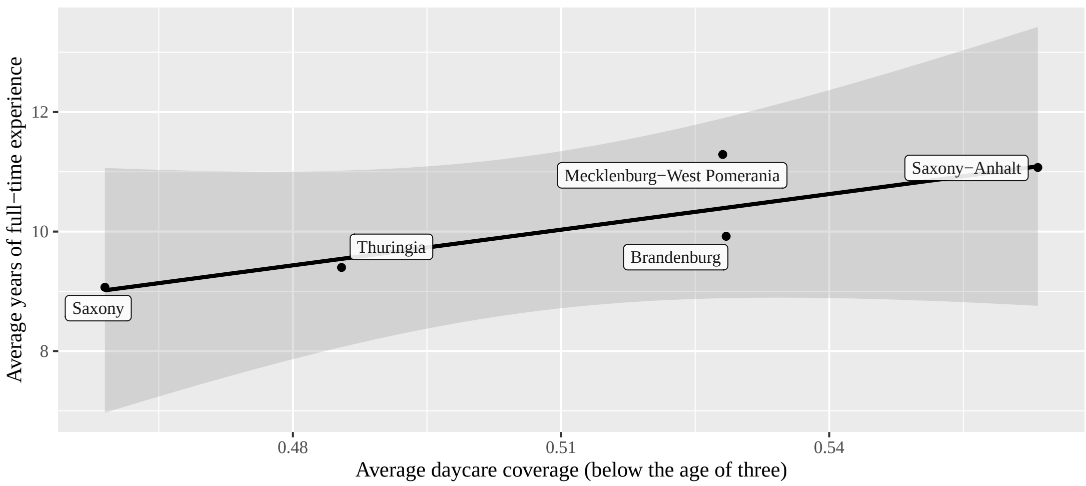
An important challenge in this context is that there is an almost tautological connection between a mother's labor supply and the family's use of daycare. Children need constant supervision such that, if both parents work, others need to take care of their children which almost always includes some formal daycare. Thus, there are very limited insights to be drawn from a regression of maternal labor supply on *individual* usage of daycare services. For this reason, I do not use microdata on daycare usage but apply two alternative strategies to gauge the role of daycare for experience accumulation. One strategy builds on daycare availability (rather than individual usage) and the other one on regional differences in typical daycare entry ages.

First, I exploit regional differences in daycare availability *within* East Germany. If daycare is the prime factor behind mothers' experience accumulation, one should expect more accumulation in areas where daycare places are relatively abundant and less of it where they are relatively scarce. Ideally, one would use data on a relatively fine geographical level such as ZIP codes or counties, yet, I have to settle for the level of federal states (thereby implicitly assuming that places are distributed relatively evenly within states). Figure 3.8 shows that there is a remarkably clear relation between daycare availability and female labor-market experience within East Germany.[76] On the horizontal axis, I display the average daycare attendance rates for children below the age of three by federal state between 2007 and 2019 reported by the Federal Statistical Office (2022b, Table ZR8). Because of the excess demand for daycare in Germany, aggregate usage can be understood as supply of public daycare.[77] On the vertical axis, I display the average maternal full-time experience by federal state in East Germany, where I focus on mothers born in or after 1970 who are 35 to 45 years old between 2010 and 2019. There is a clear positive correlation between daycare coverage and full-time experience of mothers in East Germany, illustrated by the black regression line. The

[76]Berlin is excluded.

[77]In all of Germany, there is excess demand for child care below the age of three (Wrohlich 2008). Since 2016, the German Youth Institute (DJI) has provided yearly reports that show that actual attendance rates are below parental needs for external care for children under the age of three (see, e.g. Kayed, Wieschke, and Kuger 2023). Similarly, Geis-Thöne (2023) documents the lack of daycare places for 2023. Hence, attendance rates are likely close to the actual supply rates for child care.

Figure 3.8. Average child care coverage and mother's full-time experience by federal state.



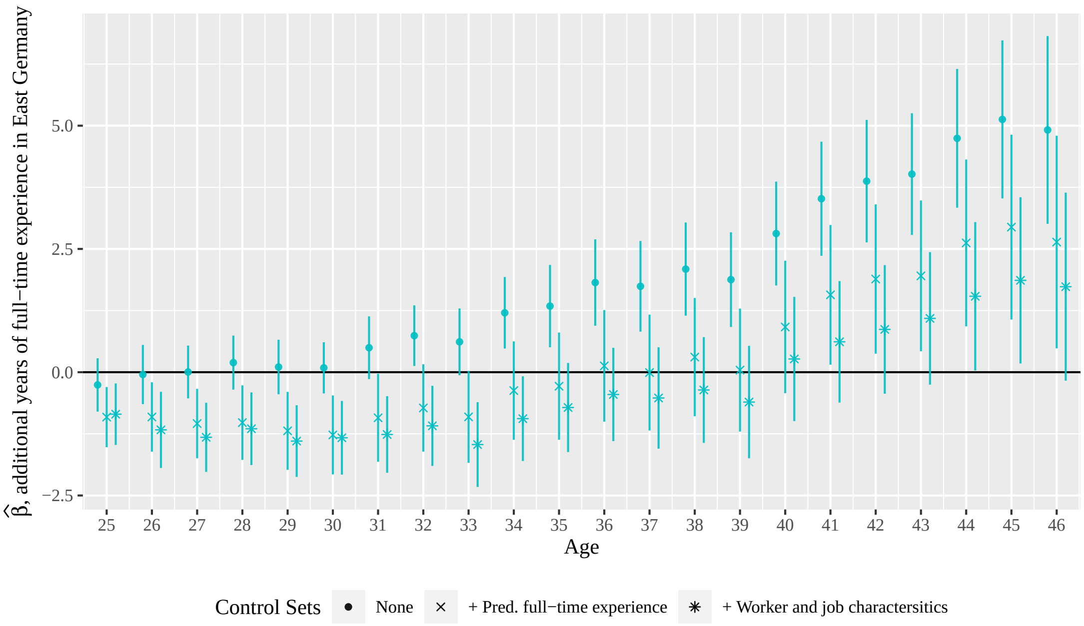
Notes: Dots show weighted averages by federal state. The regression line is plotted with a 99% confidence interval. Sample of mothers living in East Germany and born in or after 1970, who are between 35 and 45 years old during 2010 to 2019 ($n = 3765$).

higher the supply of daycare, the more years of full-time experience mothers in East Germany accumulate.

Now, I use this relation to address the question whether East German women would have the (small) experience levels of West Germany if they faced the (low) supply of young-age daycare prevalent in West Germany. To this end, I first estimate an age-specific relation between daycare supply and accumulated experience in East Germany. Specifically, I run a regression of years of full-time experience on the average daycare coverage at the federal state level, age, and the interaction of the two in a sample of mothers living in East Germany and born in or after 1970. Then, I use this relation to determine, for every mother, a predicted experience level based on the daycare supply in the federal state in which she lives.[78] For East German women, this merely takes out some idiosyncratic variation. For West German women, however, it determines the experience they would have accumulated if they reacted to daycare supply like East German women do. Conditional on the hypothesis that daycare supply is the prime factor behind the high experience levels in East Germany, East-West differences in accumulated experience should disappear if I control for these predicted experience

[78] Negative values for predicted experience are set to 0.

Figure 3.9. Years of full-time experience with predicted experience, mothers of young birth cohort.



Notes: Dots are point estimates with 95% confidence intervals based on heteroscedasticity robust standard errors of $\widehat{\beta}_{gy}$ from equation (3.7), using years of full-time experience as dependent variable. Different sets of controls are indicated by point shape. Details on predicted full-time experience are provided in the main text. The sample contains only mothers born in or after 1970 (n = 36,568, in turquoise).

levels. Hence, as a third step, I use the predicted full-time experience as an explanatory variable in the experience regression from equation (3.7).

Figure 3.9 shows the results, again for the sample of mothers in the young birth cohort. Dots indicate the estimates from the baseline regression without additional controls. As above, significant East-West differences in full-time experience emerge in the early thirties of mothers and differences accumulate to a gap of five years at the age of 46. Including predicted full-time experience (indicated by the x shape) does substantially reduce East-West differences.[79] This is in line with the hypothesis that differences in daycare are the major factor for the observed experience gaps. When adding also worker and job characteristics (asterisk shape) East-West differences further diminish. Until the mid-forties, differences remain insignificant, during the mid-forties they amount to slightly more than one year. Overall, including this very broad measure

[79]The reduction in the East-West difference is larger than for the controls considered above. For a comparison of years of full-time experience with the other control sets, see Appendix Figure 3.B.3.

of public daycare in the analysis stresses the role of the availability of external child care for the East-West experience gaps.

Daycare entry age The distinction between mothers and non-mothers in Figure (3.1) has made it obvious that children are a prime factor behind the East-West gap in accumulated labor-market experience of women. Daycare supply as a potential channel through which children affect their mothers' labor supply differently across regions has a particular implication regarding the shape of the relation between the number of children and mothers' experience, which I now turn to test. While it is a natural starting point to think in terms of linear or at least monotonic relation, the daycare supply channel implies a relation between children and experience that is unambiguous only at the extensive margin.

To understand this, consider the following stylized description of women's behavior along the daycare supply channel. Let women interrupt their working careers from the birth of their first child until their youngest child reaches the typical daycare entry age in their region, denoted by E_r, and let mothers of multiple children give birth every two years. Then, the length of the career interruption of a woman with $N > 0$ children is given by

$$E_r + (N - 1) \cdot 2,$$

and, after having returned to work, her accumulated experience at age h is

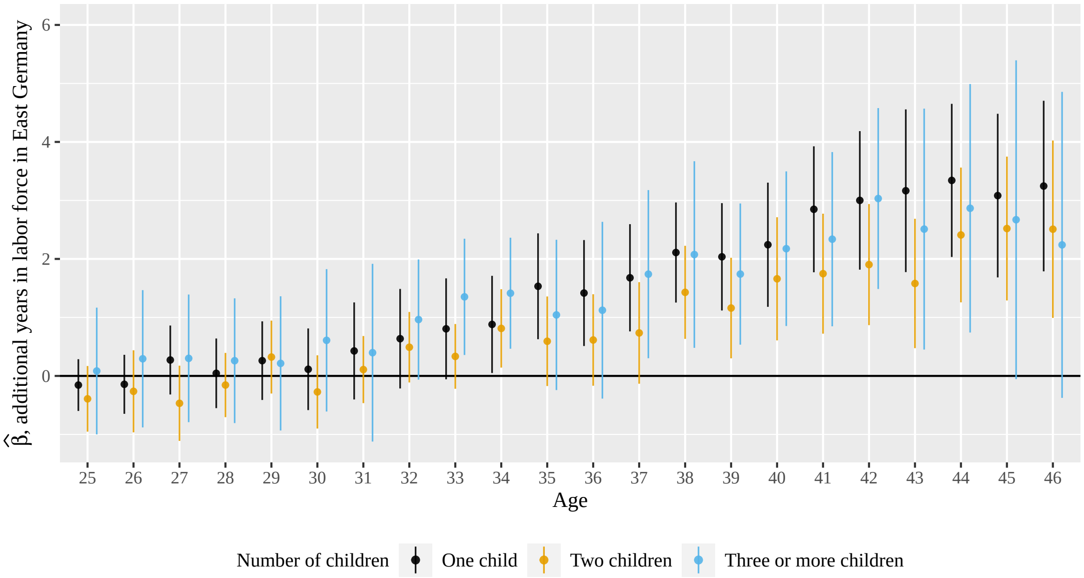
$$h - educ - 6 - E_r - (N - 1) \cdot 2,$$

where *educ* is years of education and the subtraction of six reflects the usual school entry age. Thus, the experience gap between mothers in East and West Germany with the same numbers of children, age and education is

$$\Delta_N = E_E - E_W,$$

where E_E and E_W are the daycare entry ages in East and West Germany, respectively. The key insight is that the number of children drops out. Thus, conditional on a

Figure 3.10. Years in labor force, women by number of children over the life cycle.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. Sample of women born in or after 1970 who report a positive number of children over the life cycle (n = 44,570). The color indicates the number of children over the life cycle: one child (black, n = 14,578), two children (yellow, n = 19,829) and three or more children (light blue, n = 10,163).

positive number of children, the gap is independent of the specific number of children. The hypothesis implies that the East-West gap does not differ between, e.g., mothers of two children and mothers of one child. I now test this implication.

Figure 3.10 shows the life-cycle experience gaps of women in the post-1970s birth cohort sample by the number of children over the life cycle (indicated by color). Since the individuals were born in or after 1970, we can assume that most of them gave birth in reunified Germany, hence the same parental leave policies applied.[80] The accumulated experience gaps are strikingly similar for mothers with different numbers of children across all age groups. Independent of the number of children, the experience gap between East and West German mothers at age 45 is roughly two and a half to

[80]As noted in the introduction, in Germany, the federal government is responsible for establishing and funding family policies like maternity protection, parental leave (*Elternzeit*), and parental allowances (*Elterngeld*). Although the federal government establishes the primary guidelines for childcare standards and provides additional funding, daycare falls under the jurisdiction of the federal states and municipalities. This leads to a large regional variation in the availability and scope of daycare in Germany.

three years.[81] This is exactly the result, that the daycare supply channel implies: the accumulated experience gap is the same for mothers with one, two, or more children.

Quantitatively, the gap of two years is in line with the daycare supply channel as many East German children enter daycare in the summer after their first birthday while most West German children used to enter in the summer after they turned three, thus two years later than their peers in the East.[82] The gap in Figure 3.10 is only slightly larger (roughly two to three years). To summarize, the results of the two evaluations regarding daycare supply are well in line with it being the prime factor behind the strong accumulation of labor-market experience of women in East Germany.

3.5.3 Estimation results for men

The previous analysis has documented pronounced differences in labor-market experience between East and West German women, in particular, mothers. I now investigate whether men or fathers in East Germany contribute to this gap. It could be that East German men (fathers) reduce their labor supply and thereby enable their female partners to work more than their West German counterparts. Whether this potential explanation is relevant is an empirical question and hence interesting to examine.

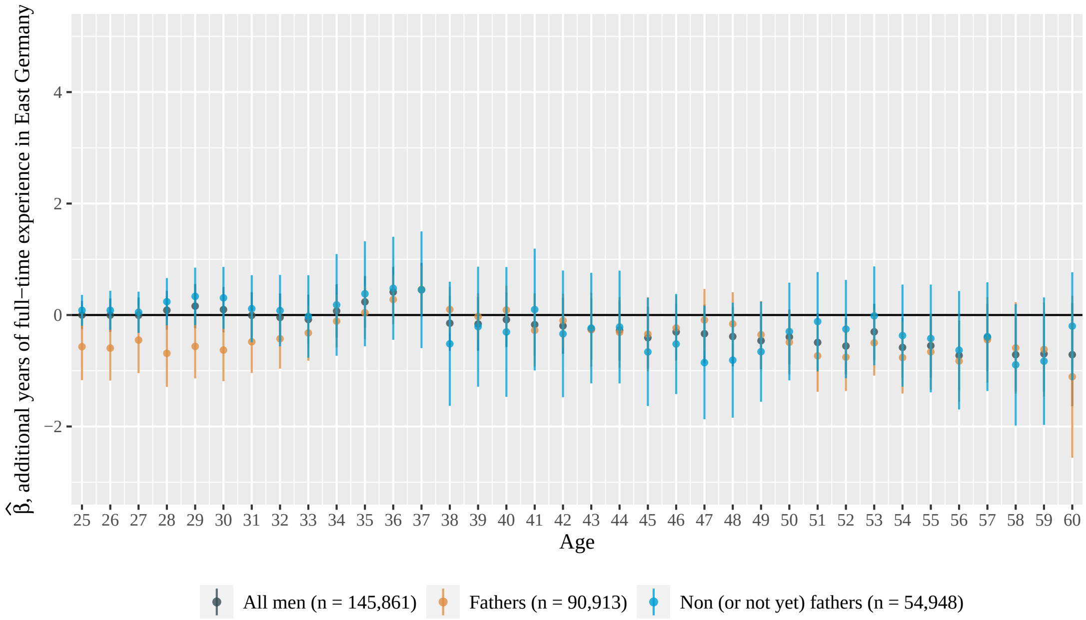
Full-time experience Similar to the analysis of women's experience gaps, I estimate equation (3.7) on samples of men, aged between 20 and 60. Again, I start with years of full-time experience as dependent variable in a regression without further covariates. If East German fathers spent less time in full-time employment than West German fathers, the coefficients on the interaction effect would be *negative*.

Figure 3.11 shows the estimated interaction-term coefficients β_{gy} for all men (dark blue), for fathers (gold) and for non- or not yet fathers (sky blue). East German men (dark blue) do *not* accumulate significantly fewer years of full-time experience than their West German counterparts. There is a slight negative trend for the older age groups, but differences are not significant. A similar picture emerges for fathers (gold) in Figure 3.11. East German fathers accumulate at most one year fewer of full-time experience than

[81] Adding controls does not affect the experience gaps, Appendix Figure 3.B.6 provides details.

[82] This is in line with data on child care coverage for children under the age of three in Germany. Since decades, attendance rates for children under the age of 3 are substantially larger in East Germany (36% in 1998, 41% in 2007, 52% in 2019) than in West Germany (3% in 1998, 10% in 2007, 30% in 2019), see Dittrich, Peucker, and Schneider (2002) and Federal Statistical Office (2022b).

Figure 3.11. Years of full-time experience, men.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using full-time experience as dependent variable. Standard errors are heteroscedasticity robust. I consider three samples: All men (dark blue), men who have children (gold), and men who do not (yet) have children (sky blue).

their West German counterparts. The small negative gap is statistically significant for fathers only in their early thirties, it then vanishes after their mid-thirties and reappears in their early fifties. For non-fathers (sky blue), there are no significant differences.[83]

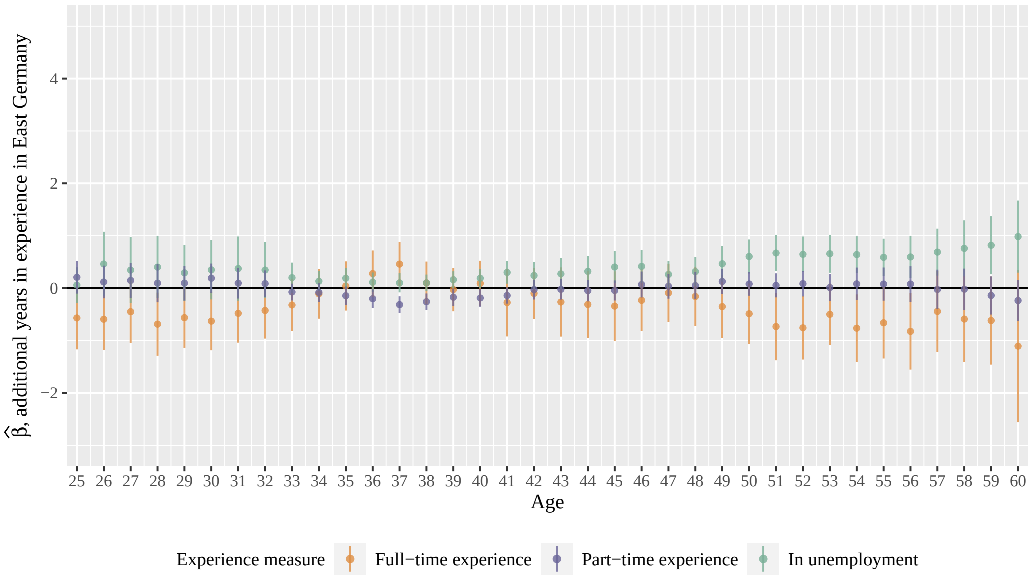
Part-time experience, years in unemployment Even when the results for full-time employment do not support the hypothesis that East German fathers interrupt their careers more strongly than West German fathers, there might be differences for fathers in other forms of employment.

Working in part-time employment enables fathers to (potentially) take up more unpaid responsibilities in the household, such as child care.[84] However, if East German fathers are part-time employed more often than West German fathers, that would be in support of East German fathers enabling their female partners to work. It is therefore

[83]See Appendix Figure 3.B.7 for a multi-panel version of Figure 3.11 and Appendix Table 3.B.3 for the complete regression models.

[84]Bünning (2020) shows that fathers in Germany who work part-time are more involved in housework and childcare at home. Involvement in child care and housework substantially decreases when fathers return to full-time work.

Figure 3.12. Years of full-time experience, of part-time experience, and in unemployment, fathers.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using full-time experience (gold), years in part-time employment (lavender), or years in unemployment (sage green) as dependent variable. Standard errors are heteroscedasticity robust. The sample contains only fathers ($n = 90{,}913$).

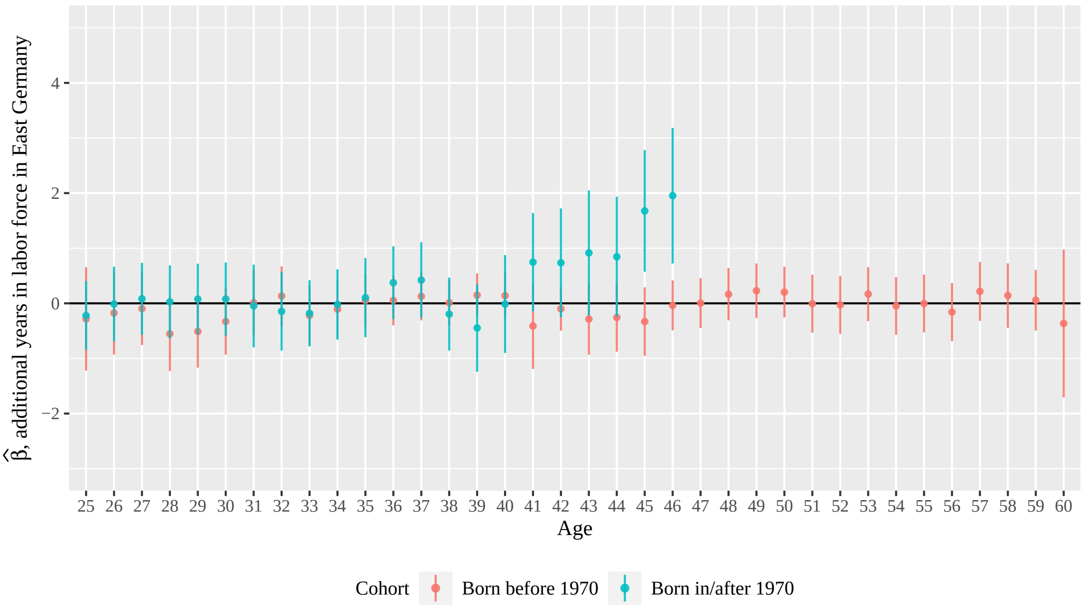
important to look beyond full-time experience. Then again, East German fathers are more exposed to unemployment risks such that full-time experience may underestimate their accumulated labor supply.

Figure 3.12 shows results for years in full-time employment (gold), part-time employment (lavender), and unemployment (sage green) for fathers. As illustrated above, East German fathers accumulate slightly fewer years of full-time experience (gold) than their West German counterparts. However, there are no differences in part-time employment (lavender) between East and West men or fathers. Yet, the aggregated view taken in Figures 3.11 and 3.12 may mask some East-West differences potentially occurring in subgroups. To rule this out, I repeat the sample split by birth cohort performed for mothers also for fathers. If I split the sample by birth cohort in 1970, the results for part-time experience are similar, see Figure 3.B.9.[85]

Regarding years in unemployment (sage green in Figure 3.12), East German fathers accumulate slightly more time in unemployment than their West German counterparts.

[85]If anything, East German fathers in the young post-1970s birth cohort accumulate slightly *fewer* years in part-time employment during their mid-thirties.

Figure 3.13. Years in labor force, fathers by birth cohort.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. Fathers born before 1970 (n = 63,313) are displayed in coral red, fathers born in or after 1970 (n = 26,543) are displayed in turquoise.

In the highest age groups, East German fathers have close to one year more in unemployment. At younger ages, there are no significant gaps for fathers. Again, if I split the sample by birth cohort in 1970, results are similar, see Appendix Figure 3.B.10. East-West differences in years in unemployment are larger for the younger cohort, though mostly not significant for fathers. Hence, fathers in East Germany do not interrupt their full-time employment to work in part-time employment, the observed differences are more likely related to more time in unemployment.

Years in labor force Figure 3.12 already indirectly suggests that there barely are East-West differences in total years in labor force, which is the sum of the three experience measures displayed. Lastly, Figure 3.13 shows the results for total years in the labor force for fathers by birth cohort. For fathers born before 1970, no differences arise. For fathers born in or after 1970, there emerges a positive significant gap during the mid-forties. If anything, this hints at a *higher* attachment to the labor market of East

German fathers.[86] If the hypothesis regarding potential differences in men's contribution to internal child care were quantitatively relevant, one should find clearly negative coefficients. This is not what Figure 3.13 suggests.

There is no evidence that East German fathers interrupt their careers in a way that differs from the behavior of West German fathers. In this sense, fundamental differences in the division of roles in the household cannot easily explain observed differences in work experience among mothers. My analysis provides no indication that fathers step back in their labor supply to provide informal child care any different in East Germany than in West Germany.

3.5.4 Summary of experience profile analysis

My analysis has shown that West German women, or more precisely, mothers, accumulate substantial experience gaps compared to similar East German women and mothers. At the same time, there is no evidence that East German fathers reduce their labor supply in a way that differs from the behavior of West German fathers. Thus, differences in the behavior of fathers do not help explaining the differences in work experience among mothers. Another main result of my study is that accounting for obvious control variables measuring worker and job characteristics also does not help in explaining the documented differences in the labor-supply behavior of mothers. In particular, I found that accounting for East-West differences in the industry mix and marriage rates leaves the estimated differences in various experience measures largely unaffected.

Regarding differences in external child care, I provided some evidence on the correlation between public daycare coverage and maternal labor supply in East Germany. Further, I show via a hypothetical experience measure that East-West experience differences can in large parts be explained by differences in daycare coverage. The constant experience gap across different numbers of children also strengthens the role of external daycare. Contributing to the literature discussed in Section 3.2, my analysis provides no indication that fathers step back in their labor supply to provide informal child care any different in East Germany than in West Germany. Hence, it is unlikely the case

[86] Figure 3.B.11 displays the results for years in labor force split by year of birth in 1970 including covariates for all samples of men. Overall, including sets of covariates does not affect coefficients considerably.

that an expansion in external child care would crowd out informal child care by fathers in West Germany or in East Germany any differently.

Overall, the absence of different labor supply decisions of fathers implies that informal child care by fathers in East Germany is not applicable to explain differences in labor supply histories of mothers between East and West Germany. This is an important result with implications for the role of *external* (public) child care, indirectly corroborating its role.

3.6 Conclusion

This chapter has examined differences in labor-market experience between individuals in East and West Germany. As a starter, I have shown that differences in labor-market experience contribute substantially to the gender wage gap in Germany and that experience explains by far the largest part in decompositions of the East-West "gap in the gender wage gap". Then, my analysis has shown that East German women accumulating several years more of full-time and total labor-market experience than women of the same age in West Germany cannot be explained by East-West differences in the industry mix and marriage rates. In contrast to that, including daycare in the analysis reduces East-West differences. Finally, the hypothesis that men, or fathers, in East Germany contribute to this gap by interrupting their full-time careers is not supported by the data.

Taken together, I interpret this set of results as corroborating the importance of public child care. There are still substantial differences between East and West Germany in the provision of public child care and the attitudes toward working mothers. My results underline the point of Bertrand (2020) that children are one of the remaining pain points for women in the labor market. To support mothers in their labor-market participation, the provision of public child care seems crucial.

Appendix 3.A Further details of gender wage gap analysis

Table 3.A.1. Sample means by gender and region in 2019.

	(1)	(2) Germany	(3)	(4)	(5) West Germany	(6)	(7)	(8) East Germany	(9)
	Men	Women	Δ	Men	Women	Δ	Men	Women	Δ
Number of observations	4416	5214		3571	4189		845	1025	
Real hourly wage (€)	18.7	15.3	3.4	19.4	15.6	3.8	15.2	13.9	1.3
Log real hourly wage	2.82	2.63	0.19	2.85	2.64	0.21	2.63	2.54	0.09
Years of full-time experience	17.9	10.8	7.2	17.8	10.2	7.6	18.5	13.8	4.7
Years of part-time experience	1.2	6.7	-5.5	1.2	7.0	-5.8	1.3	5.1	-3.9
Years of tenure	10.8	9.6	1.1	10.9	9.3	1.6	9.9	11.3	-1.4
Years of education	12.6	12.8	-0.2	12.6	12.8	-0.1	12.6	12.8	-0.2

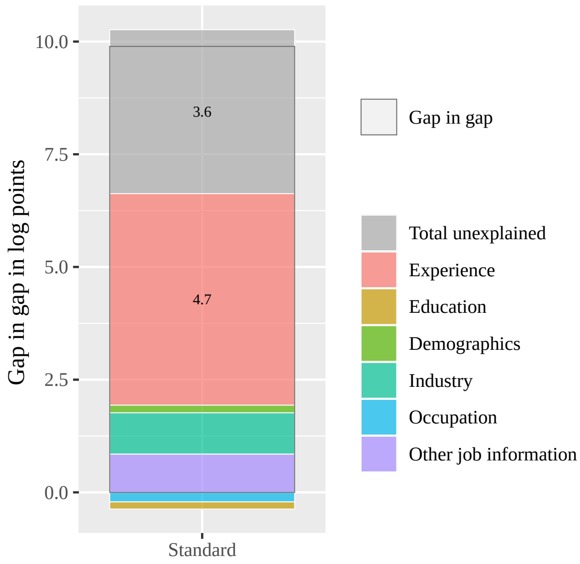
Notes: Gender and region specific sample sizes and weighted averages for selected variables. Columns (1), (2),(4), (5), (7), and (8) show averages by gender and region. Columns (3), (6), and (9) show male average minus female average. The sample contains only employed individuals.

Table 3.A.1 shows gender- and region-specific sample sizes and weighted means for selected variables in 2019. The log real hourly wage shows the raw gender wage gap by region in columns (3), (6), and (9).

Figure 3.A.1. Decomposition of gender wage gap, sample of full-time employed individuals.

Notes: Figure 3.A.1 shows the standard decomposition of the gender wage gap for Germany in 2019 on a sample of full-time employed individuals. The total of the colored areas corresponds to $\widehat{\Delta}|_X$, the gray colored area of the bar indicates $\widehat{\Delta}|_\beta$. Colors indicate variable groups.

Figure 3.A.2. Decomposition of gap in gap, Γ, sample of full-time employed.



Notes: Figure 3.A.2 shows $\widehat{\Gamma}$ from equation (3.6), the "gap in the gap", in a sample of full-time employed individuals in 2019 and its decomposition into an explained and unexplained part.

Figure 3.A.1 provides the wage-gap decomposition in a sample of full-time employed individuals. In line with my baseline results, I find that the biggest share of the gender wage gap can be related to gender differences in labor-market experience.

Figure 3.A.2 shows the "gap in the gap" in a sample of full-time employed workers, i.e., the East-West gap in the gender wage gap, $\widehat{\Gamma}$, from equation (3.6), and its decomposition into an explained and unexplained part. Again, and even more pronounced in this sample of full-time employed workers, East-West differences in gender experience gaps dominate.

Appendix 3.B Further details of experience-gap analysis

Subsection 3.B.1 Detailed descriptive statistics

Table 3.1 shows gender- and region-specific sample sizes and weighted averages for all variables included in the regression analysis. Columns (1) to (4) show averages for the total sample, columns (5) to (8) show averages for the subsample of individuals with children. The first row displays the sample sizes of the different subsamples and the second row shows the sample size of the subsample relative to all women, or men, respectively.

The average age is 40 for both men and women in East and West Germany. Only in the subsample of parents, the average age is slightly larger (42 years), but also here no substantial differences arise.

The next group of variables in Table 3.B.1 contains demographics. The average survey year is reported for completeness to ensure that the samples are also similar in that respect. I include the current marriage status of the individual and whether the individual has ever been married. East and West German women have marriage rates at roughly 60%. In the sample of mothers, this share increases by almost 16% points to 73% in West Germany and by only 10% points in East Germany.[87] For men and fathers, marriage rates are lower in East Germany. The shares of individuals that have ever been married are larger in West Germany across all samples.

I also include the number of children over the life cycle of the individual. On average, East German women have more children (1.6) than West German women (1.4). But conditional on having children, West German mothers have more children (2.0) than East German mothers (1.9). This reversal of East-West differences is not present for men. On average, men in East Germany have slightly fewer children than men in West Germany.

Regarding years of education, East German women have on average half a year of education more than women in West Germany. In East Germany, 32% of women have some tertiary education, compared to 23% in West Germany. These differences are more pronounced in the sample of mothers. I observe no difference between women and mothers in East Germany, but in West Germany education levels are even lower for mothers than for all women. Differences for men/fathers in education variables between East and West Germany are very small.

The set of “job characteristics” is the last group of variables in Table 3.B.1. Employment rates are relatively similar across regions for women and mothers. Men and fathers in West Germany have clearly higher employment rates, the East-West differences amount up to 7 percentage points. Substantial differences arise between women

[87]For completeness, compared to marriage rates, the share of couples living together is relatively similar across all samples and higher for individuals with children at roughly 80%.

Table 3.B.1. Descriptive statistics.

	Women (n = 164,369)		Men (n = 145,861)		Mothers (n = 123,307)		Fathers (n = 90,913)	
	West (1)	East (2)	West (3)	East (4)	West (5)	East (6)	West (7)	East (8)
Number of observations	125,159	39,210	112,650	33,211	91,116	32,191	70,156	20,757
Share of all women/men (%)	76.1	23.9	77.2	22.8	55.4	19.6	48.1	14.2
*Wages**								
Real hourly wage	14.6	11.7	18.6	12.6	14.7	12.2	20.1	13.7
Log real hourly wage	2.5	2.3	2.8	2.4	2.5	2.4	2.9	2.5
Experience measures								
Years in labor force	16.0	18.7	19.1	19.5	17.8	21.0	22.3	22.1
Years of full-time experience	10.3	14.1	17.8	17.7	10.3	15.8	21.0	20.5
Years of part-time experience	5.0	3.2	0.7	0.6	6.7	3.6	0.6	0.5
Years in unemployment	0.6	1.4	0.7	1.2	0.8	1.5	0.6	1.0
Demographics								
Age	40.5	40.9	41.0	41.2	43.9	43.5	44.1	43.8
Survey year	2004.8	2004.4	2005.4	2005.2	2004.7	2004.1	2006.3	2006.2
Has partner (%)	68.4	71.3	68.7	64.7	80.6	79.3	90.8	87.7
Age at birth of first child					25.4	23.2	29.1	26.5
Married	56.6	56.4	57.9	51.7	73.2	66.4	84.4	73.7
Been married	65.8	64.0	64.0	57.8	84.8	75.5	91.1	81.3
Number of kids	1.4	1.6	1.1	1.0	2.0	1.9	2.0	1.8
Years of education	12.1	12.5	12.2	12.3	11.7	12.5	12.1	12.5
Some tertiary degree (%)	23.0	32.4	28.7	28.7	19.7	33.7	31.3	32.5
Job characteristics (%)								
Employed	82.9	80.3	91.6	84.9	78.4	79.5	94.1	88.5
Working full-time	44.1	56.8	84.4	77.7	28.7	53.9	88.6	83.0
Last reported industry								
Agriculture	0.7	3.1	1.0	5.0	0.7	3.4	1.0	5.0
Energy/Mining/Other	1.7	2.0	2.8	4.1	1.4	2.0	3.0	4.1
Manufacturing	17.6	12.9	36.9	26.2	18.0	12.8	39.7	25.6
Construction	1.6	2.4	9.8	16.8	1.9	2.5	10.2	17.6
Trade	21.3	19.3	11.2	11.3	22.2	18.1	10.0	9.4
Transport	3.3	4.7	7.2	8.2	3.2	5.0	7.3	8.0
Bank, Insurance	4.8	2.6	4.1	1.4	4.2	2.6	4.0	1.6
Services	49.0	52.9	27.1	27.0	48.4	53.7	24.9	28.8
Last reported occupation								
Legislators/managers	2.7	3.4	6.0	3.6	2.0	3.4	7.0	4.3
Professionals	12.7	12.7	17.4	13.3	9.9	12.4	17.0	14.6
Technicians/associate prof.	27.9	31.3	18.8	13.6	25.4	31.8	17.8	14.0
Clerks	19.3	15.8	8.9	5.3	19.5	15.6	7.8	4.0
Service/shop workers	19.6	18.9	5.6	6.3	20.8	18.0	4.8	5.6
Skilled agric./fishery workers	0.6	2.0	0.8	2.5	0.6	2.0	0.7	2.1
Craft/trades workers	3.7	4.7	23.8	31.3	4.0	4.7	23.9	31.4
Plant/machine operators	3.3	2.9	12.3	14.4	4.0	2.9	14.3	15.1
Elementary occupations	10.2	8.3	6.4	9.7	13.7	9.2	6.7	8.8
Occupation by skill level								
Skill level: high	43.3	47.4	42.2	30.5	37.4	47.6	41.7	32.9
Skill level: medium	46.5	44.3	51.3	59.8	48.9	43.2	51.5	58.3
Skill level: low	10.2	8.3	6.4	9.7	13.7	9.2	6.7	8.8

Notes: Gender and region specific sample sizes and weighted averages for selected variables. Columns (1) to (4) show averages for all men and women, columns (5) to (8) show averages for individuals with children. I follow the ISCO standards for the definitions of skill level by occupation. *Wages are only observed for currently employed individuals, not for all observations.

in East and West Germany in the share of individuals currently working full-time. For women, full-time shares are 13 percentage points larger in East Germany, for mothers even 25 percentage points. Further, in East Germany, full-time rates for women are similar to those of mothers. In West Germany, full-time rates drop from 44% for all women to 29% for mothers. For men (fathers), full-time rates are very high at 78% (83%) and above, both in East and West Germany. Men (fathers) in East Germany have lower full-time rates compared to men (fathers) in West Germany.

Finally, Table 3.B.1 displays the employment shares of individuals by industry and occupation. The majority of women in both East and West Germany work in the service sector, followed by trade and manufacturing. There are no obvious industry differences between all women and mothers. For men, there are differences in industry shares between East and West Germany. The largest sector for West German men/fathers works is manufacturing, whereas the largest sector for East German men/fathers is the service sector (like women). The occupations displayed in Table 3.1 are sorted by descending skill level. Most women and mothers in East and West Germany work as associate professionals, clerks or service workers. Women in East Germany appear to work on average in occupations with slightly higher skill levels compared to women in West Germany. This is different for men. The share of managers, professionals and associate professionals is larger for men and fathers in West Germany than in East Germany. In occupations with lower skill levels such as craft workers or elementary occupations, the share of East German men is larger. On average, West German men work in occupations with higher skill levels than East German men. East-West differences are slightly less pronounced for fathers.

Subsection 3.B.2 Additional regression results for women

Table 3.B.2 shows the complete regression models when estimating equation (3.7), for two different dependent variables and the three subsamples of women. Columns (1) to (3) show the complete regression tables for Figures 3.1, column (5) is displayed in Figure 3.2. Columns (4) and (6) are displayed for completeness.

Table 3.B.2. Regression models in different samples of women and experience measures.

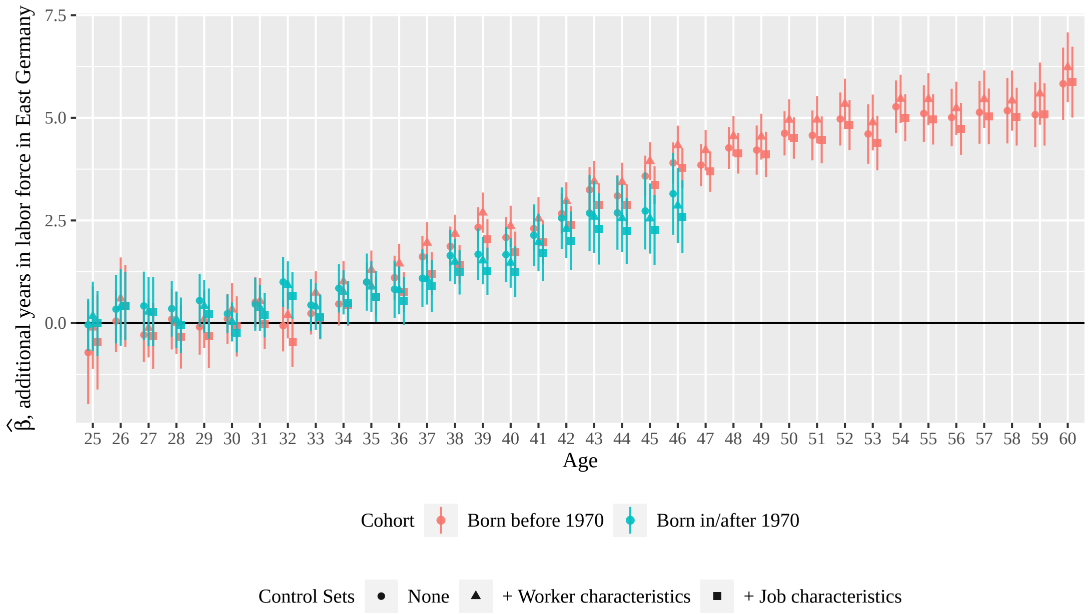
	(1)	(2)	(3)	(4)	(5)	(6)
	Years of full-time experience			Years in labor force		
	All women	Mothers	Non-mothers	All women	Mothers	Non-mothers
Age of 20	1.71 (0.16)***	1.48 (0.24)***	1.73 (0.21)***	1.33 (0.12)***	1.32 (0.20)***	1.54 (0.16)***
Age of 21	2.03 (0.16)***	1.85 (0.23)***	2.06 (0.21)***	1.83 (0.12)***	1.88 (0.22)***	2.05 (0.16)***
Age of 22	2.43 (0.16)***	2.11 (0.21)***	2.49 (0.21)***	2.41 (0.12)***	2.44 (0.19)***	2.63 (0.16)***
Age of 23	2.95 (0.16)***	2.54 (0.22)***	3.02 (0.21)***	3.06 (0.12)***	2.99 (0.19)***	3.29 (0.16)***
Age of 24	3.47 (0.16)***	2.89 (0.21)***	3.61 (0.21)***	3.79 (0.12)***	3.60 (0.18)***	4.04 (0.17)***
Age of 25	4.00 (0.17)***	3.56 (0.23)***	4.16 (0.22)***	4.45 (0.13)***	4.35 (0.20)***	4.70 (0.17)***
Age of 26	4.61 (0.17)***	4.00 (0.22)***	4.89 (0.22)***	5.15 (0.13)***	4.84 (0.19)***	5.50 (0.18)***
Age of 27	5.14 (0.17)***	4.64 (0.22)***	5.46 (0.23)***	5.83 (0.13)***	5.61 (0.18)***	6.17 (0.18)***
Age of 28	5.70 (0.17)***	5.20 (0.22)***	6.11 (0.24)***	6.56 (0.13)***	6.37 (0.18)***	6.92 (0.19)***
Age of 29	6.29 (0.18)***	5.64 (0.22)***	6.92 (0.24)***	7.34 (0.13)***	7.01 (0.17)***	7.83 (0.19)***
Age of 30	6.80 (0.18)***	6.10 (0.21)***	7.62 (0.25)***	8.05 (0.14)***	7.69 (0.17)***	8.62 (0.20)***
Age of 31	7.30 (0.19)***	6.52 (0.22)***	8.39 (0.27)***	8.89 (0.14)***	8.48 (0.18)***	9.60 (0.21)***
Age of 32	7.81 (0.19)***	7.01 (0.22)***	9.24 (0.28)***	9.63 (0.14)***	9.19 (0.18)***	10.48 (0.22)***
Age of 33	8.19 (0.19)***	7.38 (0.22)***	9.90 (0.29)***	10.32 (0.15)***	9.85 (0.18)***	11.35 (0.23)***
Age of 34	8.61 (0.20)***	7.81 (0.23)***	10.62 (0.32)***	11.07 (0.15)***	10.55 (0.18)***	12.32 (0.25)***
Age of 35	9.02 (0.20)***	8.13 (0.23)***	11.62 (0.33)***	11.81 (0.15)***	11.25 (0.19)***	13.34 (0.25)***
Age of 36	9.43 (0.20)***	8.51 (0.23)***	12.43 (0.34)***	12.59 (0.15)***	12.03 (0.19)***	14.28 (0.26)***
Age of 37	9.82 (0.21)***	8.86 (0.24)***	13.34 (0.37)***	13.30 (0.16)***	12.65 (0.19)***	15.43 (0.27)***
Age of 38	10.32 (0.21)***	9.32 (0.24)***	14.31 (0.38)***	14.06 (0.16)***	13.39 (0.19)***	16.44 (0.29)***
Age of 39	10.69 (0.22)***	9.63 (0.24)***	15.24 (0.40)***	14.87 (0.16)***	14.11 (0.19)***	17.76 (0.28)***
Age of 40	11.34 (0.23)***	10.16 (0.25)***	16.30 (0.44)***	15.84 (0.17)***	15.09 (0.20)***	18.64 (0.32)***
Age of 41	11.83 (0.23)***	10.49 (0.25)***	17.25 (0.45)***	16.63 (0.17)***	15.81 (0.20)***	19.63 (0.31)***
Age of 42	12.41 (0.23)***	10.93 (0.25)***	18.16 (0.43)***	17.43 (0.17)***	16.60 (0.20)***	20.37 (0.32)***
Age of 43	12.72 (0.25)***	11.08 (0.26)***	19.29 (0.45)***	18.17 (0.19)***	17.23 (0.21)***	21.64 (0.33)***
Age of 44	13.15 (0.25)***	11.52 (0.26)***	20.02 (0.45)***	18.95 (0.18)***	18.02 (0.21)***	22.50 (0.34)***
Age of 45	13.86 (0.26)***	12.18 (0.27)***	20.94 (0.47)***	19.94 (0.19)***	18.99 (0.22)***	23.61 (0.33)***
Age of 46	14.54 (0.27)***	12.72 (0.28)***	22.14 (0.48)***	20.75 (0.19)***	19.72 (0.22)***	24.72 (0.33)***
Age of 47	14.90 (0.27)***	13.15 (0.29)***	22.59 (0.50)***	21.58 (0.20)***	20.65 (0.23)***	25.37 (0.36)***
Age of 48	15.63 (0.29)***	13.68 (0.30)***	23.80 (0.53)***	22.47 (0.20)***	21.39 (0.23)***	26.68 (0.38)***
Age of 49	16.13 (0.29)***	14.07 (0.30)***	25.05 (0.54)***	23.31 (0.21)***	22.22 (0.24)***	27.69 (0.39)***
Age of 50	16.53 (0.30)***	14.57 (0.31)***	25.74 (0.57)***	23.94 (0.21)***	22.85 (0.24)***	28.66 (0.39)***
Age of 51	17.02 (0.32)***	14.99 (0.33)***	26.69 (0.59)***	24.85 (0.22)***	23.75 (0.25)***	29.65 (0.41)***
Age of 52	17.52 (0.32)***	15.53 (0.33)***	27.86 (0.62)***	25.78 (0.23)***	24.68 (0.26)***	30.99 (0.38)***
Age of 53	18.13 (0.34)***	16.22 (0.35)***	28.36 (0.67)***	26.90 (0.23)***	25.85 (0.26)***	31.98 (0.39)***
Age of 54	18.68 (0.35)***	16.83 (0.38)***	28.88 (0.69)***	27.65 (0.24)***	26.65 (0.27)***	32.66 (0.46)***
Age of 55	19.19 (0.37)***	17.24 (0.39)***	30.06 (0.70)***	28.48 (0.26)***	27.45 (0.29)***	33.67 (0.50)***
Age of 56	19.74 (0.38)***	17.72 (0.40)***	30.80 (0.75)***	29.37 (0.25)***	28.29 (0.28)***	34.70 (0.51)***
Age of 57	20.46 (0.39)***	18.32 (0.41)***	31.55 (0.72)***	30.09 (0.28)***	28.95 (0.31)***	35.45 (0.50)***
Age of 58	20.68 (0.41)***	18.90 (0.43)***	31.87 (0.83)***	30.93 (0.28)***	29.97 (0.31)***	36.25 (0.58)***
Age of 59	21.42 (0.44)***	19.38 (0.47)***	33.35 (0.75)***	32.01 (0.28)***	30.96 (0.32)***	37.50 (0.51)***
Age of 60	21.50 (0.47)***	19.34 (0.50)***	33.91 (0.81)***	32.51 (0.31)***	31.46 (0.35)***	37.93 (0.56)***
Age of 20 x East	−0.18 (0.07)**	0.03 (0.29)	−0.20 (0.08)**	−0.14 (0.10)	0.53 (0.69)	−0.28 (0.07)***
Age of 21 x East	−0.25 (0.06)***	−0.05 (0.20)	−0.26 (0.07)***	−0.26 (0.07)***	−0.09 (0.24)	−0.33 (0.07)***
Age of 22 x East	−0.20 (0.08)**	−0.04 (0.17)	−0.19 (0.09)*	−0.24 (0.08)**	−0.39 (0.19)*	−0.22 (0.09)*
Age of 23 x East	−0.13 (0.10)	−0.10 (0.18)	−0.03 (0.11)	−0.10 (0.09)	−0.23 (0.18)	−0.05 (0.10)
Age of 24 x East	−0.19 (0.10)	−0.04 (0.17)	−0.05 (0.12)	−0.18 (0.10)	−0.21 (0.18)	−0.08 (0.12)
Age of 25 x East	−0.17 (0.13)	−0.12 (0.22)	−0.00 (0.15)	−0.07 (0.11)	−0.10 (0.21)	0.02 (0.14)
Age of 26 x East	−0.26 (0.14)	0.20 (0.22)	−0.30 (0.18)	−0.02 (0.12)	0.25 (0.21)	−0.10 (0.16)
Age of 27 x East	−0.22 (0.16)	0.04 (0.22)	−0.17 (0.23)	0.15 (0.14)	0.21 (0.20)	0.25 (0.20)
Age of 28 x East	−0.20 (0.16)	0.15 (0.21)	−0.22 (0.25)	0.23 (0.15)	0.22 (0.18)	0.42 (0.24)
Age of 29 x East	−0.20 (0.17)	0.25 (0.21)	−0.18 (0.28)	0.30 (0.15)*	0.40 (0.18)*	0.52 (0.27)
Age of 30 x East	−0.16 (0.18)	0.34 (0.19)	−0.18 (0.34)	0.28 (0.15)	0.28 (0.17)	0.75 (0.30)*
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of full-time experience			Years in labor force		
	All women	Mothers	Non-mothers	All women	Mothers	Non-mothers
Age of 31 x East	0.06 (0.19)	0.80 (0.22)***	−0.48 (0.36)	0.33 (0.17)	0.49 (0.19)*	0.55 (0.34)
Age of 32 x East	0.22 (0.19)	0.92 (0.21)***	−0.25 (0.44)	0.42 (0.16)**	0.65 (0.18)***	0.54 (0.37)
Age of 33 x East	0.52 (0.20)**	1.20 (0.22)***	0.16 (0.46)	0.67 (0.17)***	0.84 (0.19)***	1.11 (0.36)**
Age of 34 x East	0.95 (0.21)***	1.63 (0.23)***	0.41 (0.50)	0.75 (0.17)***	1.01 (0.19)***	0.89 (0.43)*
Age of 35 x East	1.24 (0.22)***	2.04 (0.24)***	0.22 (0.53)	0.98 (0.18)***	1.32 (0.19)***	0.89 (0.48)
Age of 36 x East	1.56 (0.24)***	2.40 (0.25)***	0.56 (0.59)	1.02 (0.18)***	1.33 (0.20)***	1.29 (0.52)*
Age of 37 x East	1.95 (0.24)***	2.85 (0.25)***	0.24 (0.62)	1.32 (0.18)***	1.69 (0.20)***	1.27 (0.50)*
Age of 38 x East	2.17 (0.24)***	3.19 (0.25)***	−0.30 (0.68)	1.66 (0.17)***	2.12 (0.18)***	1.09 (0.55)*
Age of 39 x East	2.55 (0.26)***	3.60 (0.26)***	−0.43 (0.78)	1.87 (0.18)***	2.41 (0.19)***	0.85 (0.59)
Age of 40 x East	2.64 (0.27)***	3.83 (0.28)***	−0.68 (0.87)	1.84 (0.19)***	2.36 (0.20)***	1.04 (0.55)
Age of 41 x East	3.12 (0.28)***	4.43 (0.29)***	−0.42 (0.92)	2.24 (0.19)***	2.79 (0.20)***	1.46 (0.48)**
Age of 42 x East	3.51 (0.29)***	4.90 (0.29)***	0.10 (0.93)	2.63 (0.19)***	3.21 (0.20)***	1.77 (0.51)***
Age of 43 x East	4.19 (0.31)***	5.79 (0.31)***	−0.55 (0.96)	2.99 (0.21)***	3.69 (0.22)***	1.46 (0.52)**
Age of 44 x East	4.71 (0.32)***	6.29 (0.33)***	0.08 (0.95)	3.16 (0.20)***	3.81 (0.21)***	1.88 (0.42)***
Age of 45 x East	4.73 (0.34)***	6.39 (0.34)***	−0.45 (1.02)	3.30 (0.20)***	4.02 (0.22)***	1.60 (0.43)***
Age of 46 x East	5.05 (0.35)***	6.88 (0.36)***	−0.67 (1.01)	3.49 (0.21)***	4.33 (0.23)***	1.15 (0.54)*
Age of 47 x East	5.43 (0.37)***	7.14 (0.38)***	0.11 (1.00)	3.54 (0.24)***	4.24 (0.26)***	1.97 (0.48)***
Age of 48 x East	5.81 (0.39)***	7.85 (0.40)***	−1.15 (1.12)	3.96 (0.23)***	4.83 (0.24)***	1.59 (0.52)**
Age of 49 x East	5.50 (0.43)***	7.57 (0.44)***	−1.38 (1.15)	3.80 (0.26)***	4.68 (0.28)***	1.31 (0.54)*
Age of 50 x East	6.07 (0.45)***	8.01 (0.46)***	−0.17 (1.10)	4.18 (0.26)***	5.10 (0.28)***	1.22 (0.56)*
Age of 51 x East	6.41 (0.47)***	8.40 (0.48)***	−0.22 (1.21)	4.28 (0.27)***	5.18 (0.29)***	1.33 (0.61)*
Age of 52 x East	7.00 (0.46)***	9.01 (0.48)***	−1.01 (1.19)	4.48 (0.29)***	5.40 (0.31)***	0.91 (0.60)
Age of 53 x East	6.92 (0.49)***	8.82 (0.51)***	−0.87 (1.20)	4.25 (0.32)***	5.11 (0.34)***	0.78 (0.67)
Age of 54 x East	7.45 (0.50)***	9.35 (0.52)***	−0.96 (1.33)	4.78 (0.29)***	5.66 (0.31)***	0.72 (0.76)
Age of 55 x East	7.81 (0.52)***	9.83 (0.54)***	−1.24 (1.44)	4.86 (0.31)***	5.73 (0.33)***	1.21 (0.79)
Age of 56 x East	7.66 (0.56)***	9.79 (0.58)***	−1.80 (1.47)	4.66 (0.35)***	5.58 (0.37)***	0.78 (0.83)
Age of 57 x East	7.91 (0.57)***	10.24 (0.59)***	−2.44 (1.51)	5.18 (0.33)***	6.18 (0.36)***	1.02 (0.85)
Age of 58 x East	8.25 (0.62)***	10.18 (0.64)***	−1.28 (1.65)	5.07 (0.42)***	5.83 (0.45)***	1.91 (0.82)*
Age of 59 x East	8.46 (0.64)***	10.68 (0.66)***	−1.96 (1.70)	5.30 (0.34)***	6.21 (0.36)***	1.09 (0.86)
Age of 60 x East	9.03 (0.69)***	11.32 (0.71)***	−0.89 (1.75)	5.85 (0.38)***	6.76 (0.41)***	2.14 (0.82)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.74	0.74	0.88	0.93	0.92	0.95
Adj. R^2	0.74	0.74	0.88	0.93	0.92	0.95
Num. obs.	164,369	123,307	41,062	164,369	123,307	41,062

Notes: Table 3.B.2 displays the regression from equation (3.7) estimated for full-time experience and years in labor force on different samples of women. Heteroscedasticity robust standard errors are in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

For completeness, I also consider a sample of currently employed women, which yields a sample that is more similar to the one used for the analysis of the gender wage gap in Section 3.4. By focusing on currently employed mothers, I rule out that the large experience gaps are driven by (probably West German) mothers who do not return to the labor market at all. Figure 3.B.1 displays the results (years in labor force) for currently employed mothers split by cohort. I find that focusing on only currently employed women yields similar patterns as in the baseline sample.

Figure 3.B.1. Years in labor force, currently employed mothers by birth cohort.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate mothers born before 1970 (coral red, n = 67,591) and mothers born in or after 1970 (turquoise, n = 28,126). Different sets of controls are indicated by point shape.

Figure 3.B.2 shows the results for years in the labor force for all subsamples of women.[88]

Figures 3.B.3, 3.B.4, and 3.B.5 show the results for the splitted samples for years of of full-time experience, part-time experience and years in unemployment, respectively. Overall, and in line with the results discussed in the main text, the analysis of the younger cohort yields in general similar patterns as for the older cohort.

The reduction in point estimates is slightly stronger for full-time experience, see Figure 3.B.3. Interestingly, including job characteristics reduces East-West differences considerably for the older cohort, coral red in Figure 3.B.3. However, this impact disappears when labor-force experience is considered, see Figure 3.B.2.

Figure 3.B.6 shows the results for experience gaps by number of children over the life cycle including control sets. Again, including the control sets does not affect the coefficients. Hence, Figure 3.10 in the main text is sufficient without displaying controls although not controlling for education levels.

[88]The sample sizes are as follows: for all women, born before 1970 (n = 99,071) and born in or after 1970 (n = 63,341); for mothers, (84,203) and (37,726); and for non-mothers, (14,868) and (25,615).

Subsection 3.B.3 Additional regression results for men

Table 3.B.3 shows the complete regression models when estimating equation (3.7), for two different dependent variables and the three subsamples of men. Columns (1) to (3) show the complete regression tables for Figures 3.11. Columns (4) to (6) show the regression models for years in labor force.

Table 3.B.3. Regression models with different experience measures and in different samples of men.

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of full-time experience			Years in labor force		
	All men	Fathers	Non-fathers	All men	Fathers	Non-fathers
Age of 20	2.12 (0.12)***	1.34 (0.31)***	2.62 (0.15)***	1.65 (0.11)***	1.17 (0.38)**	1.91 (0.14)***
Age of 21	2.46 (0.12)***	2.12 (0.34)***	2.96 (0.15)***	2.11 (0.11)***	2.30 (0.31)***	2.36 (0.14)***
Age of 22	2.80 (0.12)***	2.72 (0.30)***	3.28 (0.15)***	2.64 (0.11)***	2.77 (0.30)***	2.88 (0.14)***
Age of 23	3.26 (0.12)***	3.47 (0.29)***	3.71 (0.15)***	3.24 (0.12)***	3.68 (0.31)***	3.45 (0.14)***
Age of 24	3.76 (0.12)***	4.39 (0.30)***	4.15 (0.16)***	3.89 (0.12)***	4.65 (0.31)***	4.05 (0.14)***
Age of 25	4.35 (0.13)***	4.94 (0.25)***	4.69 (0.16)***	4.62 (0.12)***	5.35 (0.23)***	4.73 (0.15)***
Age of 26	5.01 (0.13)***	5.64 (0.23)***	5.29 (0.17)***	5.36 (0.12)***	6.00 (0.22)***	5.42 (0.15)***
Age of 27	5.69 (0.14)***	6.37 (0.23)***	5.90 (0.17)***	6.15 (0.13)***	6.75 (0.21)***	6.16 (0.16)***
Age of 28	6.42 (0.14)***	7.26 (0.23)***	6.52 (0.18)***	6.93 (0.13)***	7.71 (0.21)***	6.85 (0.16)***
Age of 29	7.18 (0.15)***	8.00 (0.22)***	7.18 (0.19)***	7.76 (0.13)***	8.49 (0.20)***	7.57 (0.17)***
Age of 30	8.10 (0.15)***	8.89 (0.21)***	7.97 (0.19)***	8.63 (0.13)***	9.26 (0.20)***	8.38 (0.17)***
Age of 31	9.06 (0.15)***	9.64 (0.22)***	8.91 (0.20)***	9.62 (0.13)***	9.99 (0.20)***	9.38 (0.18)***
Age of 32	9.99 (0.15)***	10.56 (0.21)***	9.70 (0.21)***	10.55 (0.14)***	10.89 (0.20)***	10.22 (0.18)***
Age of 33	10.98 (0.15)***	11.41 (0.21)***	10.59 (0.22)***	11.53 (0.14)***	11.81 (0.19)***	11.09 (0.19)***
Age of 34	11.92 (0.15)***	12.19 (0.21)***	11.48 (0.22)***	12.53 (0.14)***	12.61 (0.20)***	12.15 (0.20)***
Age of 35	12.80 (0.15)***	12.98 (0.20)***	12.36 (0.24)***	13.42 (0.14)***	13.41 (0.19)***	13.06 (0.21)***
Age of 36	13.72 (0.16)***	13.84 (0.21)***	13.29 (0.25)***	14.41 (0.14)***	14.34 (0.19)***	14.10 (0.22)***
Age of 37	14.77 (0.16)***	14.82 (0.21)***	14.33 (0.26)***	15.41 (0.14)***	15.34 (0.20)***	15.00 (0.23)***
Age of 38	15.96 (0.16)***	15.88 (0.21)***	15.64 (0.27)***	16.57 (0.14)***	16.38 (0.19)***	16.29 (0.23)***
Age of 39	17.01 (0.16)***	17.01 (0.20)***	16.44 (0.30)***	17.53 (0.15)***	17.42 (0.19)***	17.05 (0.26)***
Age of 40	17.97 (0.17)***	17.90 (0.21)***	17.45 (0.32)***	18.50 (0.15)***	18.29 (0.20)***	18.17 (0.26)***
Age of 41	19.07 (0.17)***	19.03 (0.21)***	18.44 (0.31)***	19.62 (0.15)***	19.36 (0.20)***	19.40 (0.27)***
Age of 42	20.22 (0.17)***	20.13 (0.21)***	19.71 (0.32)***	20.76 (0.15)***	20.44 (0.20)***	20.65 (0.26)***
Age of 43	21.20 (0.17)***	21.05 (0.22)***	20.86 (0.32)***	21.75 (0.15)***	21.42 (0.20)***	21.70 (0.27)***
Age of 44	22.29 (0.17)***	22.12 (0.21)***	21.99 (0.33)***	22.88 (0.15)***	22.49 (0.20)***	22.96 (0.26)***
Age of 45	23.37 (0.17)***	23.21 (0.21)***	23.10 (0.33)***	23.95 (0.15)***	23.53 (0.20)***	24.08 (0.26)***
Age of 46	24.49 (0.17)***	24.33 (0.22)***	24.22 (0.31)***	24.97 (0.15)***	24.59 (0.20)***	25.03 (0.25)***
Age of 47	25.47 (0.18)***	25.35 (0.22)***	25.18 (0.32)***	26.04 (0.15)***	25.63 (0.20)***	26.18 (0.24)***
Age of 48	26.49 (0.17)***	26.37 (0.22)***	26.21 (0.30)***	27.10 (0.15)***	26.70 (0.20)***	27.20 (0.24)***
Age of 49	27.60 (0.17)***	27.40 (0.23)***	27.46 (0.28)***	28.13 (0.15)***	27.73 (0.21)***	28.24 (0.23)***
Age of 50	28.65 (0.17)***	28.56 (0.22)***	28.39 (0.29)***	29.11 (0.15)***	28.80 (0.21)***	29.09 (0.24)***
Age of 51	29.65 (0.18)***	29.56 (0.23)***	29.40 (0.29)***	30.21 (0.15)***	29.88 (0.22)***	30.23 (0.23)***
Age of 52	30.80 (0.18)***	30.69 (0.23)***	30.57 (0.29)***	31.29 (0.15)***	30.97 (0.22)***	31.28 (0.23)***
Age of 53	31.70 (0.18)***	31.63 (0.23)***	31.46 (0.29)***	32.24 (0.15)***	31.98 (0.22)***	32.17 (0.23)***
Age of 54	32.78 (0.18)***	32.66 (0.25)***	32.67 (0.29)***	33.32 (0.16)***	33.04 (0.23)***	33.32 (0.23)***
Age of 55	33.67 (0.19)***	33.61 (0.25)***	33.51 (0.28)***	34.20 (0.16)***	33.96 (0.23)***	34.16 (0.24)***
Age of 56	34.68 (0.19)***	34.66 (0.25)***	34.51 (0.30)***	35.24 (0.17)***	35.03 (0.23)***	35.19 (0.26)***
Age of 57	35.61 (0.19)***	35.39 (0.27)***	35.70 (0.29)***	36.24 (0.16)***	35.83 (0.23)***	36.43 (0.24)***
Age of 58	36.57 (0.20)***	36.23 (0.28)***	36.81 (0.29)***	37.20 (0.17)***	36.73 (0.24)***	37.46 (0.25)***
Age of 59	37.50 (0.20)***	37.17 (0.28)***	37.72 (0.29)***	38.27 (0.17)***	37.73 (0.25)***	38.60 (0.25)***
Age of 60	38.33 (0.22)***	37.99 (0.31)***	38.59 (0.33)***	39.24 (0.19)***	38.65 (0.28)***	39.67 (0.27)***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of full-time experience			Years in labor force		
	All men	Fathers	Non-fathers	All men	Fathers	Non-fathers
Age of 20 x East	−0.39 (0.07)***	−0.01 (0.36)	−0.40 (0.07)***	−0.39 (0.06)***	−0.09 (0.43)	−0.37 (0.06)***
Age of 21 x East	−0.34 (0.07)***	−0.59 (0.43)	−0.32 (0.07)***	−0.39 (0.07)***	−0.93 (0.47)*	−0.35 (0.07)***
Age of 22 x East	−0.27 (0.08)***	−0.30 (0.43)	−0.27 (0.08)***	−0.32 (0.09)***	−0.20 (0.41)	−0.31 (0.09)***
Age of 23 x East	−0.14 (0.09)	−0.62 (0.41)	−0.11 (0.10)	−0.15 (0.10)	0.01 (0.37)	−0.18 (0.10)
Age of 24 x East	−0.03 (0.11)	−0.58 (0.37)	0.03 (0.11)	0.01 (0.11)	−0.05 (0.36)	−0.00 (0.11)
Age of 25 x East	−0.00 (0.13)	−0.57 (0.31)	0.08 (0.14)	0.03 (0.13)	−0.30 (0.27)	0.04 (0.15)
Age of 26 x East	−0.00 (0.15)	−0.59 (0.30)*	0.09 (0.18)	0.16 (0.15)	−0.01 (0.27)	0.10 (0.18)
Age of 27 x East	−0.00 (0.16)	−0.45 (0.30)	0.05 (0.19)	0.21 (0.16)	0.04 (0.25)	0.16 (0.18)
Age of 28 x East	0.09 (0.18)	−0.69 (0.31)*	0.24 (0.22)	0.38 (0.16)*	−0.19 (0.24)	0.45 (0.19)*
Age of 29 x East	0.16 (0.20)	−0.56 (0.29)	0.33 (0.26)	0.59 (0.16)***	−0.18 (0.24)	0.79 (0.20)***
Age of 30 x East	0.10 (0.21)	−0.63 (0.28)*	0.31 (0.28)	0.51 (0.17)**	−0.09 (0.23)	0.68 (0.23)**
Age of 31 x East	−0.01 (0.21)	−0.48 (0.29)	0.11 (0.31)	0.39 (0.18)*	−0.01 (0.24)	0.51 (0.25)*
Age of 32 x East	−0.04 (0.22)	−0.43 (0.27)	0.08 (0.33)	0.48 (0.17)**	0.01 (0.23)	0.74 (0.25)**
Age of 33 x East	−0.08 (0.23)	−0.32 (0.25)	−0.03 (0.38)	0.30 (0.17)	−0.20 (0.21)	0.72 (0.28)*
Age of 34 x East	0.07 (0.25)	−0.11 (0.24)	0.18 (0.47)	0.45 (0.18)*	−0.06 (0.21)	1.04 (0.31)***
Age of 35 x East	0.24 (0.24)	0.04 (0.24)	0.38 (0.48)	0.58 (0.17)***	0.09 (0.21)	1.26 (0.29)***
Age of 36 x East	0.41 (0.23)	0.28 (0.23)	0.48 (0.47)	0.63 (0.16)***	0.19 (0.19)	1.30 (0.28)***
Age of 37 x East	0.45 (0.25)	0.46 (0.22)*	0.45 (0.53)	0.70 (0.17)***	0.25 (0.19)	1.44 (0.30)***
Age of 38 x East	−0.15 (0.25)	0.10 (0.21)	−0.52 (0.57)	0.28 (0.18)	−0.06 (0.18)	0.92 (0.38)*
Age of 39 x East	−0.16 (0.25)	−0.03 (0.21)	−0.21 (0.55)	0.41 (0.18)*	−0.04 (0.19)	1.30 (0.36)***
Age of 40 x East	−0.08 (0.25)	0.09 (0.22)	−0.30 (0.59)	0.45 (0.19)*	0.09 (0.20)	1.22 (0.39)**
Age of 41 x East	−0.17 (0.29)	−0.27 (0.33)	0.10 (0.56)	0.24 (0.25)	−0.12 (0.32)	0.99 (0.38)**
Age of 42 x East	−0.19 (0.26)	−0.10 (0.25)	−0.34 (0.58)	0.29 (0.18)	0.11 (0.20)	0.69 (0.37)
Age of 43 x East	−0.25 (0.28)	−0.26 (0.34)	−0.23 (0.51)	0.26 (0.23)	−0.01 (0.29)	0.83 (0.39)*
Age of 44 x East	−0.27 (0.28)	−0.31 (0.32)	−0.22 (0.52)	0.18 (0.23)	−0.04 (0.28)	0.61 (0.38)
Age of 45 x East	−0.41 (0.28)	−0.34 (0.34)	−0.66 (0.50)	0.10 (0.23)	0.02 (0.28)	0.24 (0.36)
Age of 46 x East	−0.30 (0.26)	−0.23 (0.30)	−0.52 (0.46)	0.25 (0.19)	0.25 (0.22)	0.21 (0.34)
Age of 47 x East	−0.34 (0.27)	−0.09 (0.28)	−0.85 (0.52)	0.18 (0.18)	0.21 (0.22)	0.12 (0.34)
Age of 48 x East	−0.39 (0.27)	−0.16 (0.29)	−0.81 (0.53)	0.17 (0.19)	0.21 (0.23)	0.12 (0.34)
Age of 49 x East	−0.46 (0.26)	−0.35 (0.31)	−0.66 (0.46)	0.33 (0.19)	0.24 (0.25)	0.47 (0.30)
Age of 50 x East	−0.39 (0.25)	−0.49 (0.29)	−0.30 (0.45)	0.42 (0.18)*	0.20 (0.23)	0.76 (0.30)*
Age of 51 x East	−0.49 (0.27)	−0.73 (0.33)*	−0.12 (0.45)	0.22 (0.20)	−0.01 (0.27)	0.57 (0.31)
Age of 52 x East	−0.56 (0.26)*	−0.76 (0.31)*	−0.25 (0.45)	0.21 (0.20)	−0.02 (0.27)	0.58 (0.31)
Age of 53 x East	−0.30 (0.26)	−0.50 (0.30)	−0.02 (0.45)	0.30 (0.19)	0.17 (0.25)	0.49 (0.31)
Age of 54 x East	−0.58 (0.27)*	−0.76 (0.33)*	−0.37 (0.47)	0.09 (0.21)	−0.04 (0.27)	0.26 (0.34)
Age of 55 x East	−0.55 (0.29)	−0.66 (0.35)	−0.42 (0.49)	0.12 (0.22)	0.00 (0.27)	0.26 (0.36)
Age of 56 x East	−0.73 (0.32)*	−0.83 (0.37)*	−0.63 (0.54)	−0.02 (0.23)	−0.15 (0.27)	0.13 (0.39)
Age of 57 x East	−0.40 (0.31)	−0.44 (0.39)	−0.39 (0.50)	0.25 (0.21)	0.22 (0.27)	0.30 (0.32)
Age of 58 x East	−0.71 (0.34)*	−0.59 (0.42)	−0.89 (0.56)	0.15 (0.23)	0.15 (0.30)	0.16 (0.37)
Age of 59 x East	−0.70 (0.35)*	−0.62 (0.43)	−0.83 (0.58)	0.08 (0.22)	0.06 (0.28)	0.14 (0.37)
Age of 60 x East	−0.71 (0.47)	−1.11 (0.74)	−0.20 (0.49)	−0.14 (0.42)	−0.36 (0.68)	0.18 (0.35)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.95	0.96	0.94	0.97	0.97	0.97
Adj. R^2	0.95	0.96	0.94	0.97	0.97	0.97
Num. obs.	145,861	90,913	54,948	145,861	90,913	54,948

Notes: Table 3.B.3 displays the regression from equation (3.7) estimated for full-time experience and years in labor force on different samples of men. Heteroscedasticity robust standard errors are in parentheses.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure 3.B.7 shows the results for years of full-time experience for different samples of men. This figure is a multi-panel variant of Figure 3.11. Differences are mostly insignificant at the later part of the life cycle and the gap amounts to at most one year.

Figure 3.B.8 shows the results for men by birth cohort when control variables are included, again for years of full-time experience.[89]

Similar to the analysis for women, including control variables changes the estimates on the interaction term only slightly. The pattern for fathers in the young cohort is that including more control variables results in the small but negative estimates changing to small positive estimates. Specifically any negative estimates vanish when job characteristics are controlled for. Presumably, this reflects the higher prevalence of unemployment in East Germany being picked up by the region's industry-occupation mix. If the hypothesis regarding potential differences in men's contribution to internal child care were quantitatively relevant, one should find clearly negative coefficients. This is not what Figure 3.B.8 suggests.[90]

Figure 3.B.9 shows results for years in part-time employment for men by birth cohort. There are no differences in part-time employment between East and West German men or fathers. East German fathers born after 1970 accumulate half a year *less* in part-time employment than West German fathers during their mid-thirties. But this difference levels out around the age of 40. If anything, the results point toward a temporary *higher* full-time and *lower* part-time employment of East German fathers compared to their West German counterparts. Controls do not affect the coefficients.

Figure 3.B.10 displays the differences between East and West German fathers in length in unemployment. Only in the highest age groups, East German fathers have close to one year more in unemployment. At younger ages, there are no significant gaps for fathers. If anything, East German fathers have slightly more years in unemployment. For the younger cohorts, East German fathers accumulate roughly one year more in unemployment than their West German counterparts. But these differences are mostly insignificant. It appears that unemployment gaps are higher for the younger cohort.

Figure 3.B.11 displays the results for years in labor force for men split by birth in 1970. Distinct patterns are observed between the older and younger cohorts, yet the primary finding persists: Among fathers, disparities are generally non-significant across

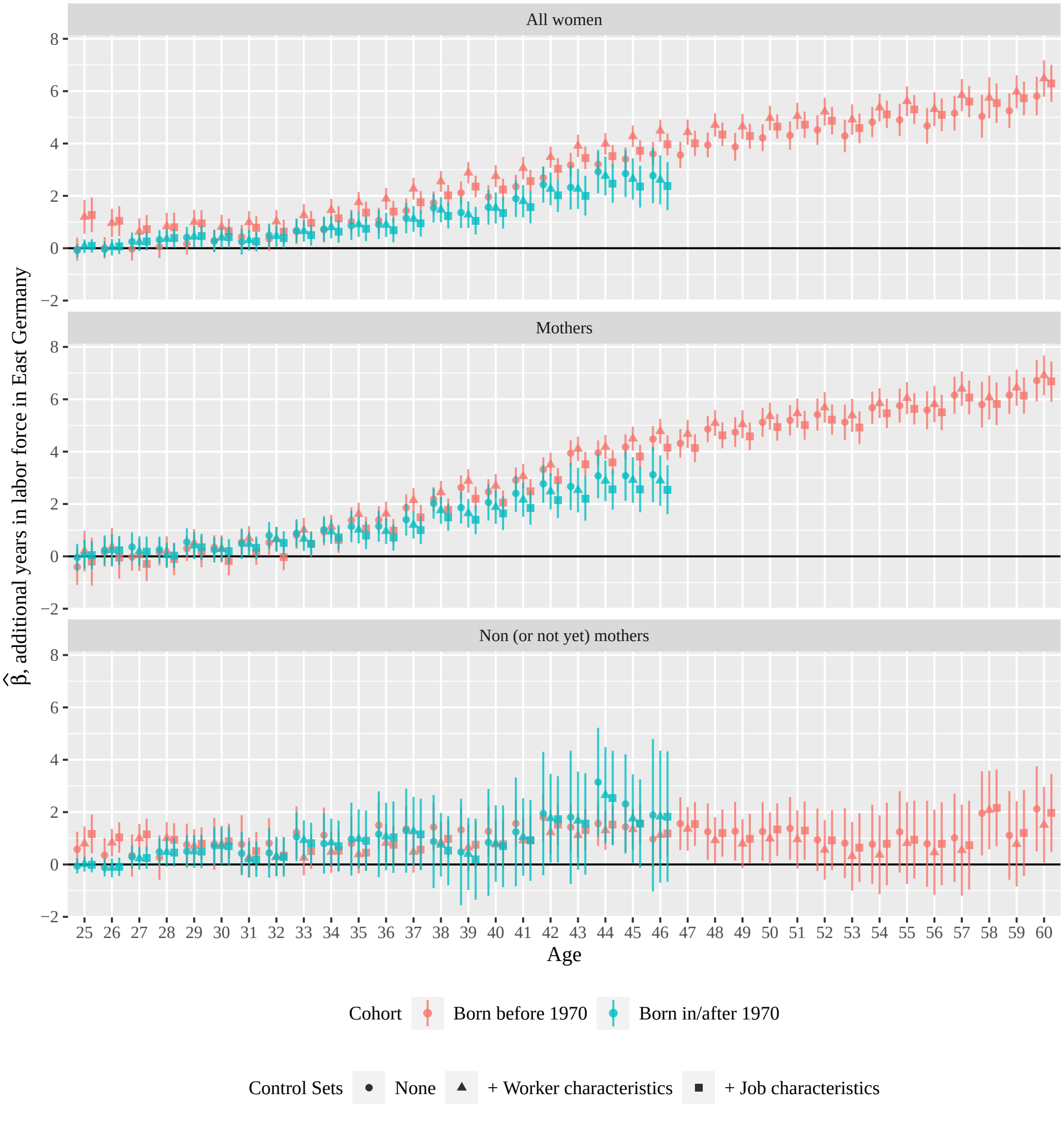
[89] The sample sizes are as follows: for all men, born before 1970 (n = 90,174) and born in or after 1970 (n = 54,203); for fathers, (63,313) and (26,543); and for non-fathers, (26,861) and (27,660).

[90] In the third specification, where I include worker and job characteristics, the point estimates for fathers below the age of 40 increase to positive levels, indicating that (young) East-German fathers have one year of full-time experience *more*. Differences are mostly insignificant at the later part of the life cycle and the gap amounts to at most one year.

most age groups. In instances where differences reach significance, East German fathers (men) exhibit a tendency to have spent more years in the labor force compared to their West German counterparts. If anything, this hints to a *higher* attachment to the labor market of East German fathers.

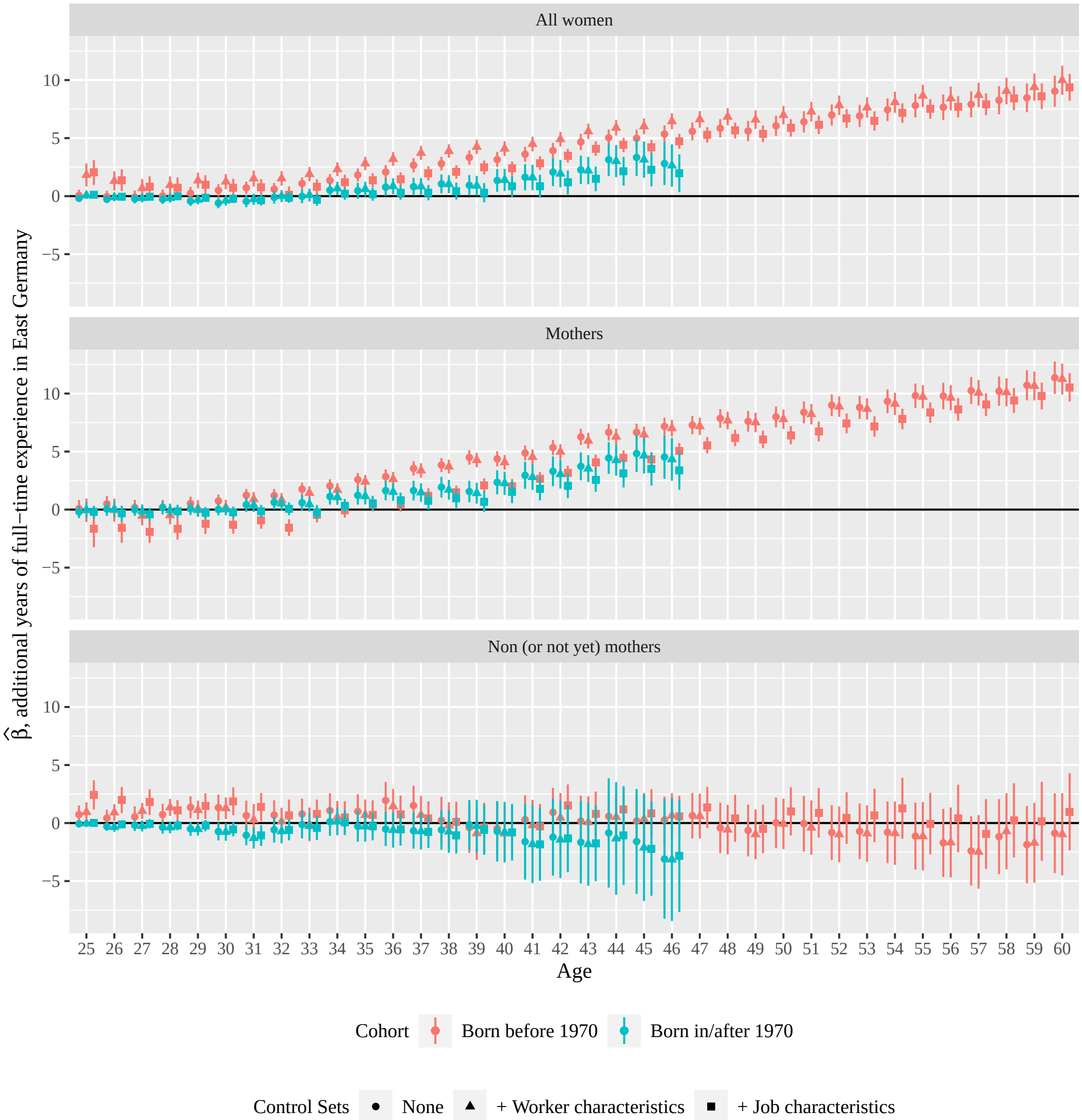
Figure 3.B.12 shows the East-West gaps years in labor force by number of children for fathers. For fathers, mostly no significant East-West differences emerge. Only fathers in East Germany with two children spent roughly two more years in the labor force compared to their West German counterparts. The additional worker and job characteristics only slightly affect the estimated coefficients. Again, fathers in East Germany work more years, not fewer, than comparable fathers in West Germany.

Figure 3.B.2. Years in labor force, women by birth cohort.



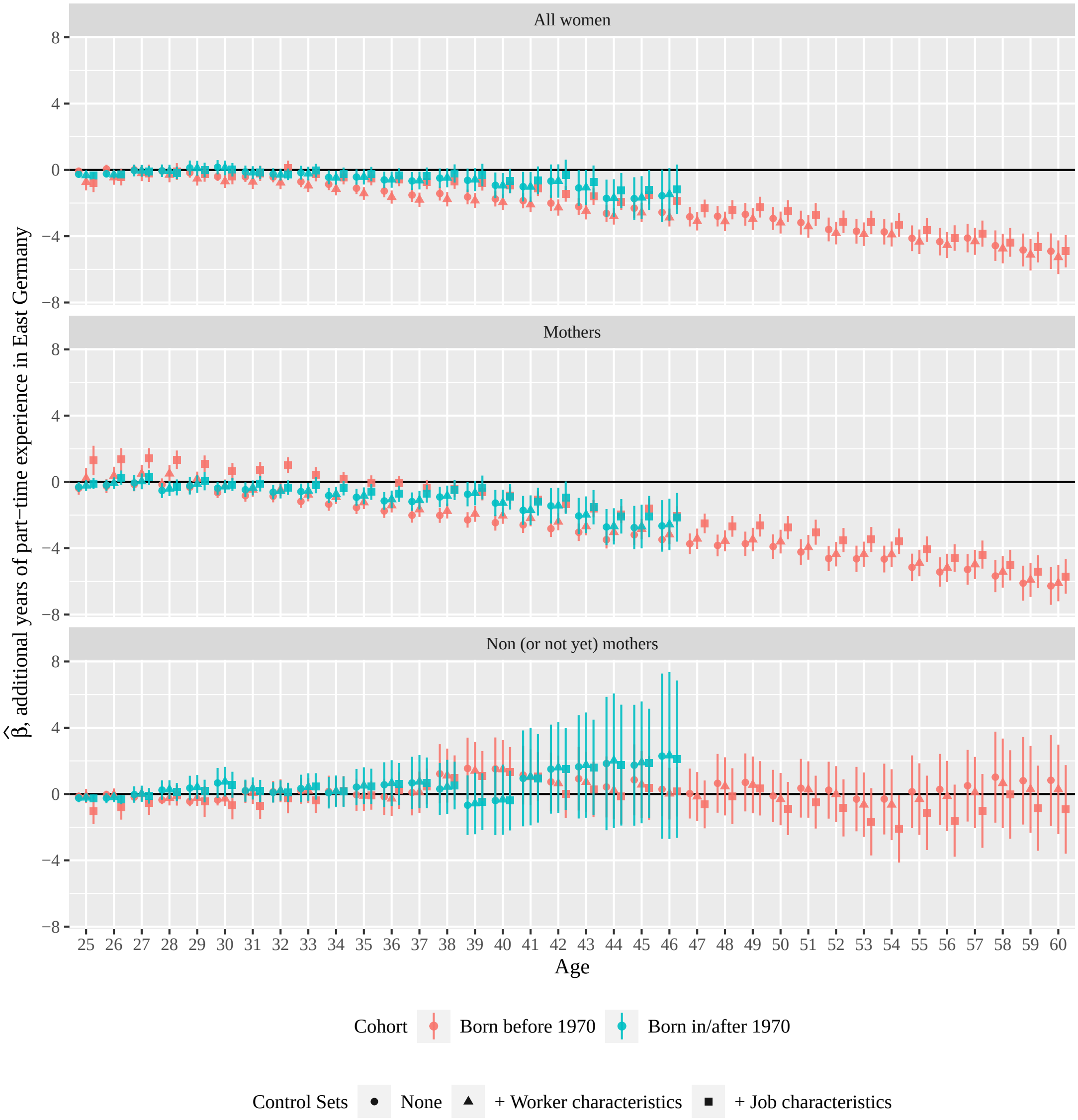
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate women born before 1970 (coral red) and women born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.3. Years of full-time experience, women by birth cohort.



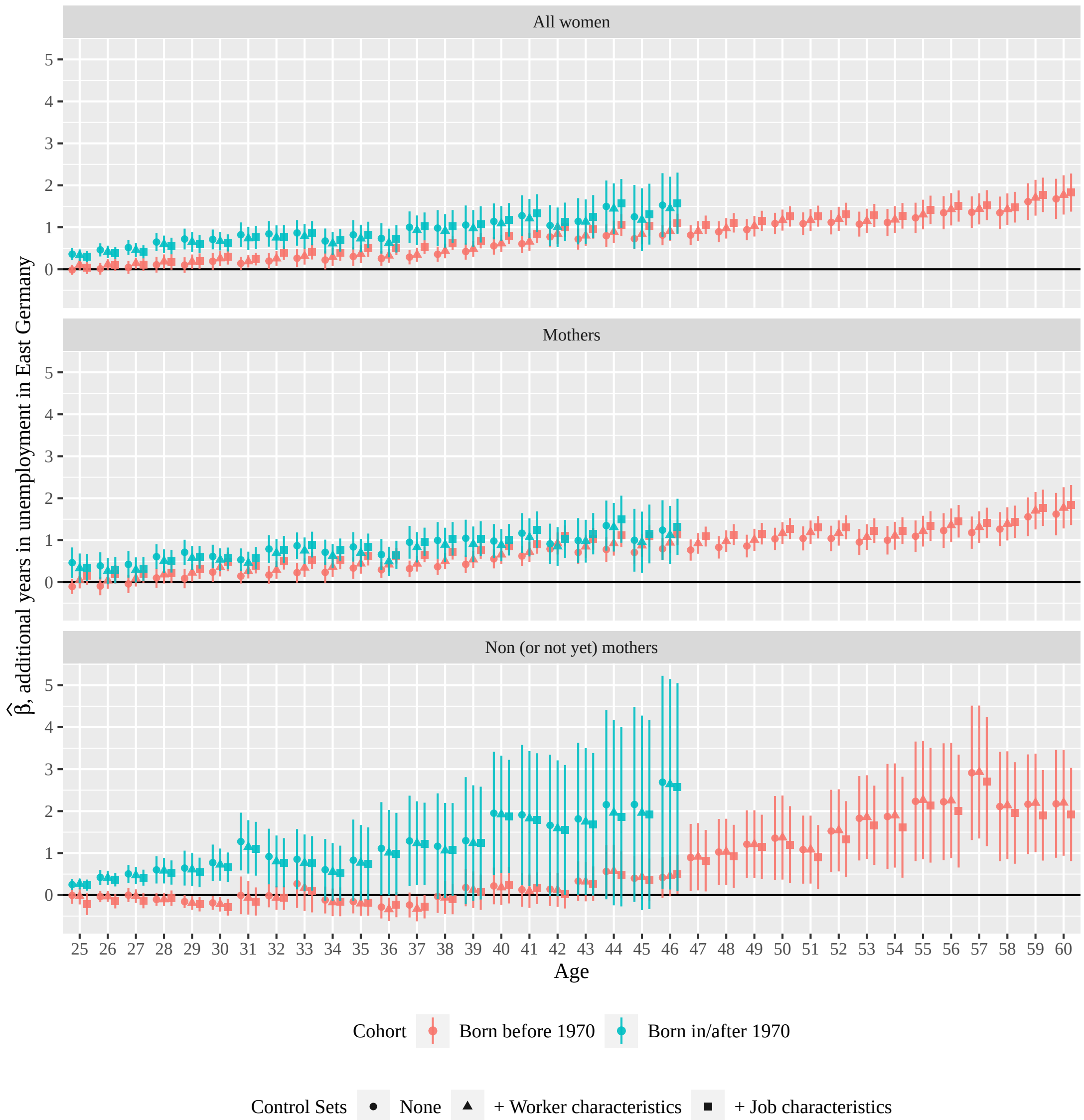
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years of full-time experience as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate women born before 1970 (coral red) and women born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.4. Years in part-time experience, women by birth cohort.



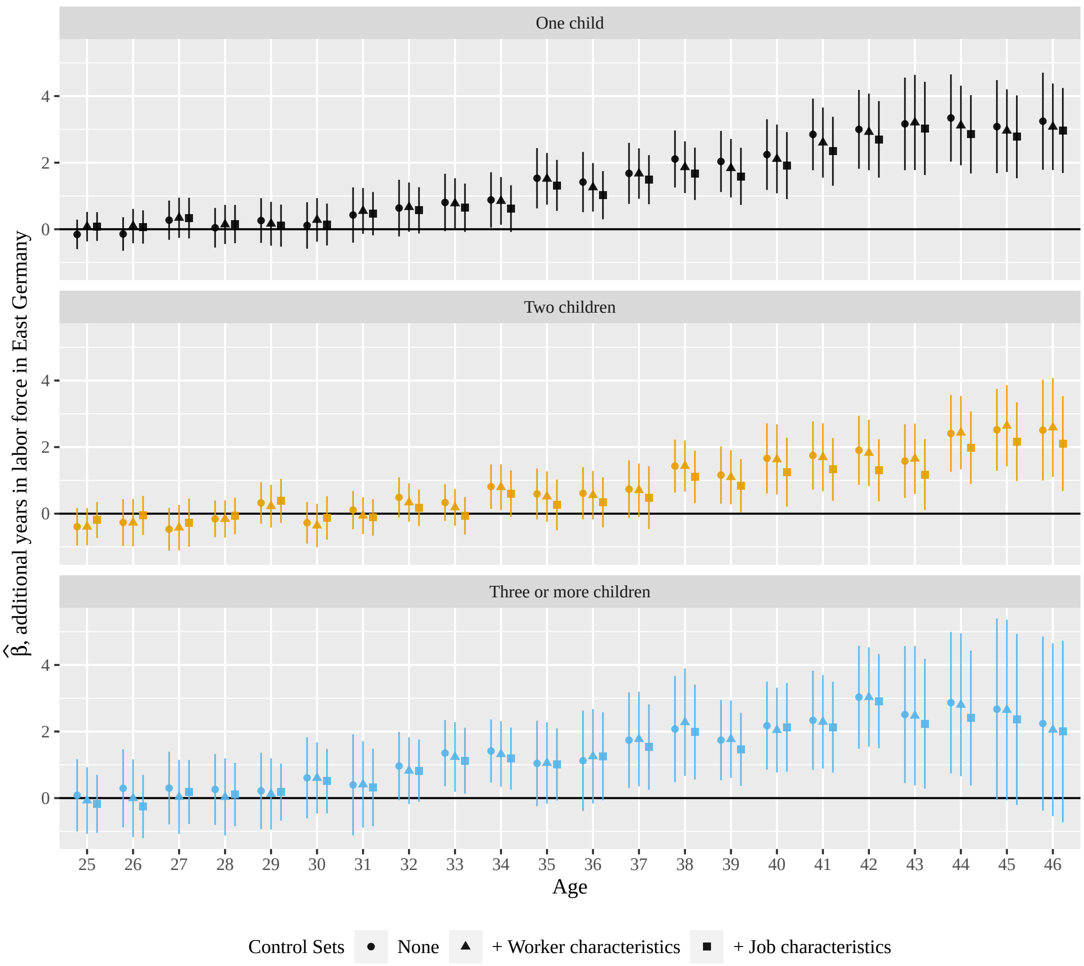
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in part-time experience as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate women born before 1970 (coral red) and women born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.5. Years in unemployment, women by birth cohort.



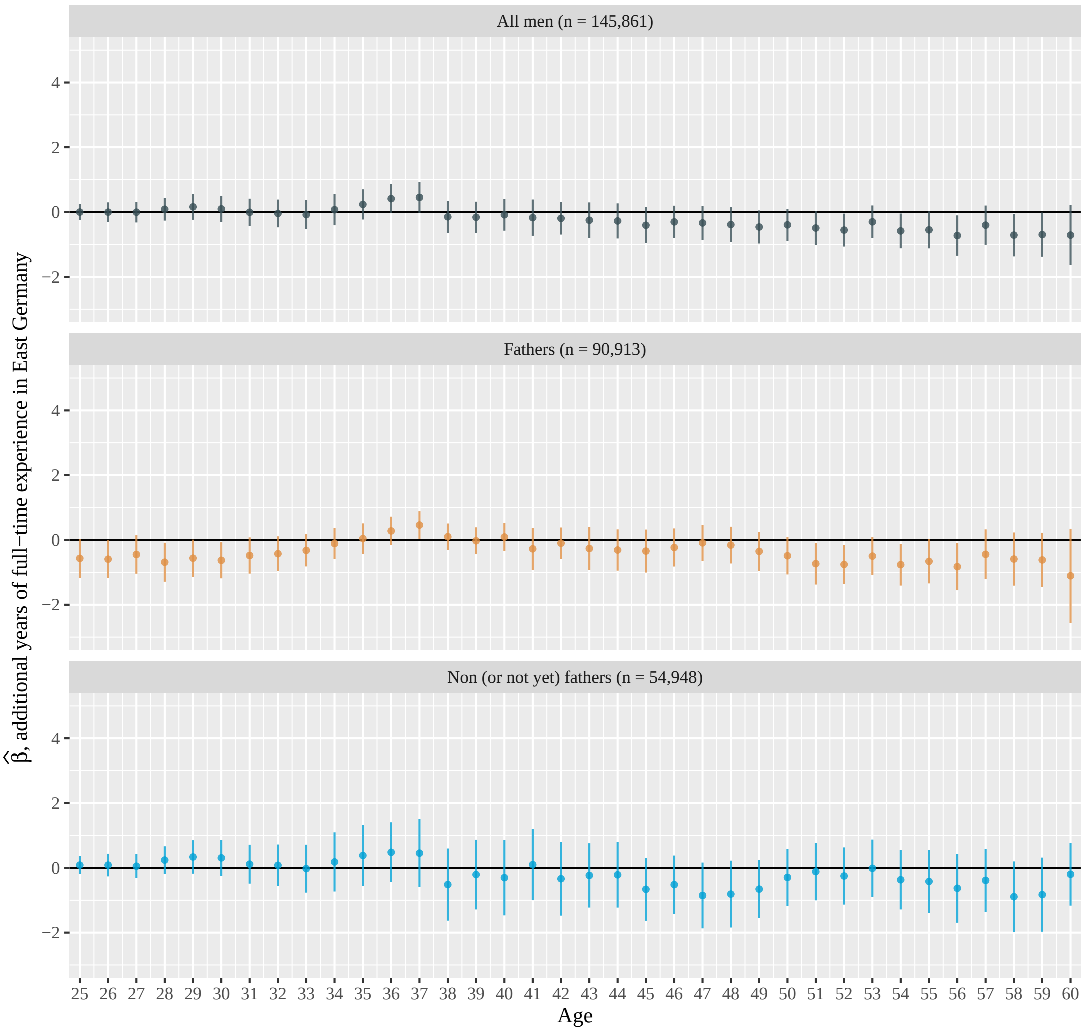
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in unemployment as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate women born before 1970 (coral red) and women born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.6. Years in labor force, women by number of children over the life cycle, with control sets.



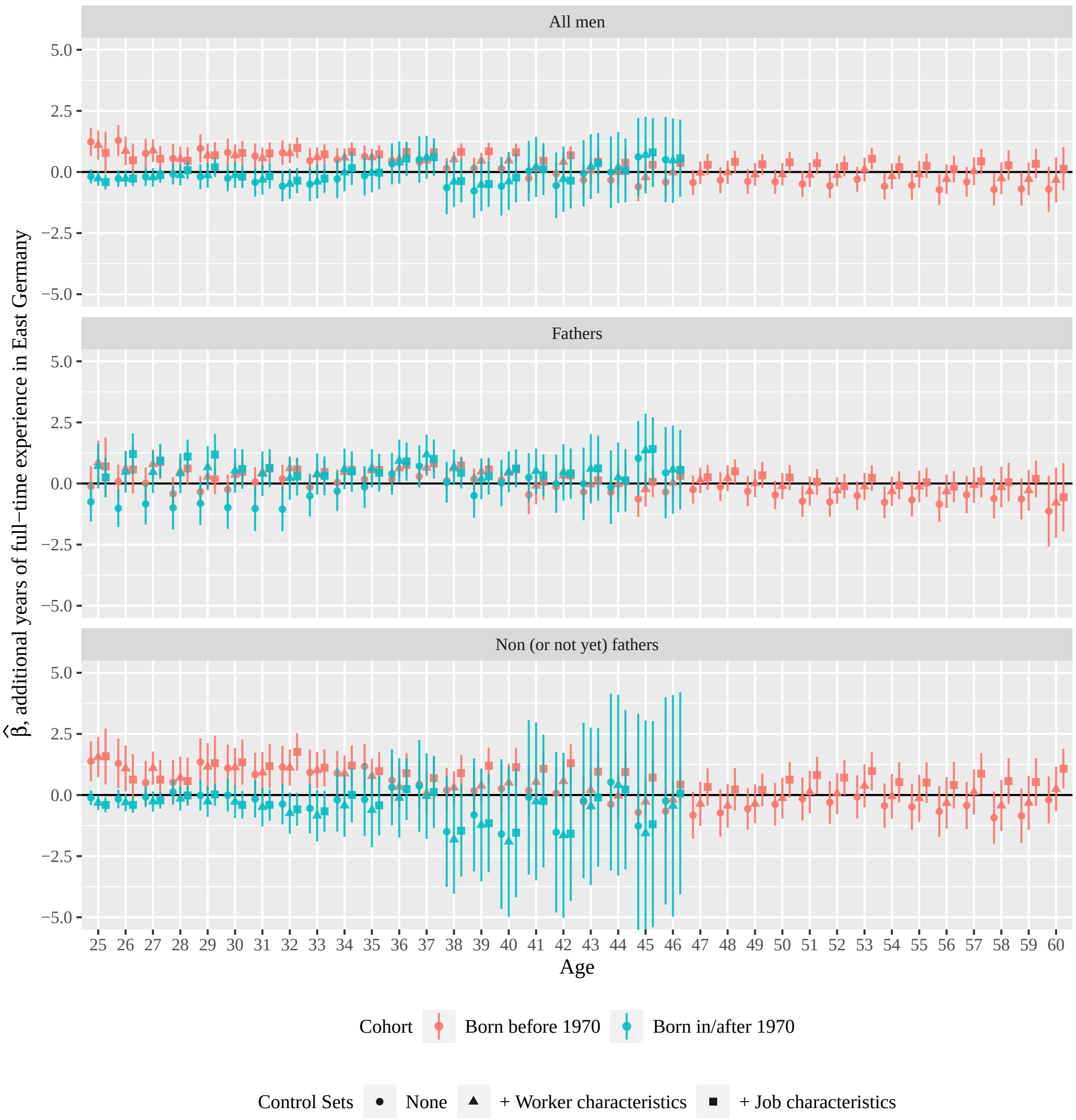
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in the labor force experience as dependent variable. Standard errors are heteroscedasticity robust. Sample of women born in or after 1970 who report a positive number of children over the life cycle (n = 44,570). The color indicates the number of children over the life cycle: one child (black, n = 14,578), two children (yellow, n = 19,829) and three or more children (light blue, n = 10,163).

Figure 3.B.7. Years of full-time experience, men.



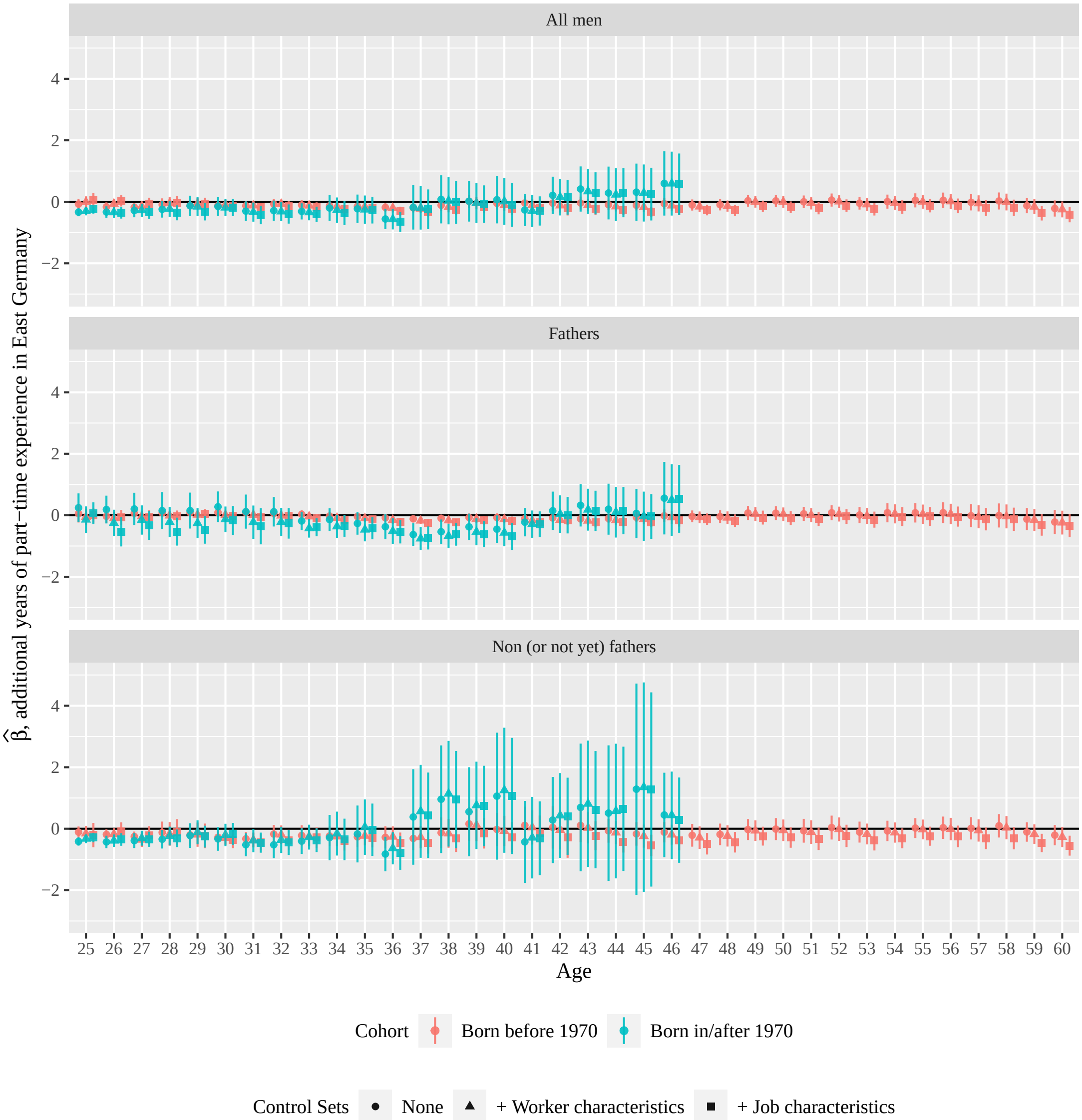
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using full-time experience as dependent variable. Standard errors are heteroscedasticity robust. I consider three samples: All men (dark blue), men who have children (gold), and men who do not (yet) have children (sky blue).

Figure 3.B.8. Years of full-time experience, men by birth cohort.



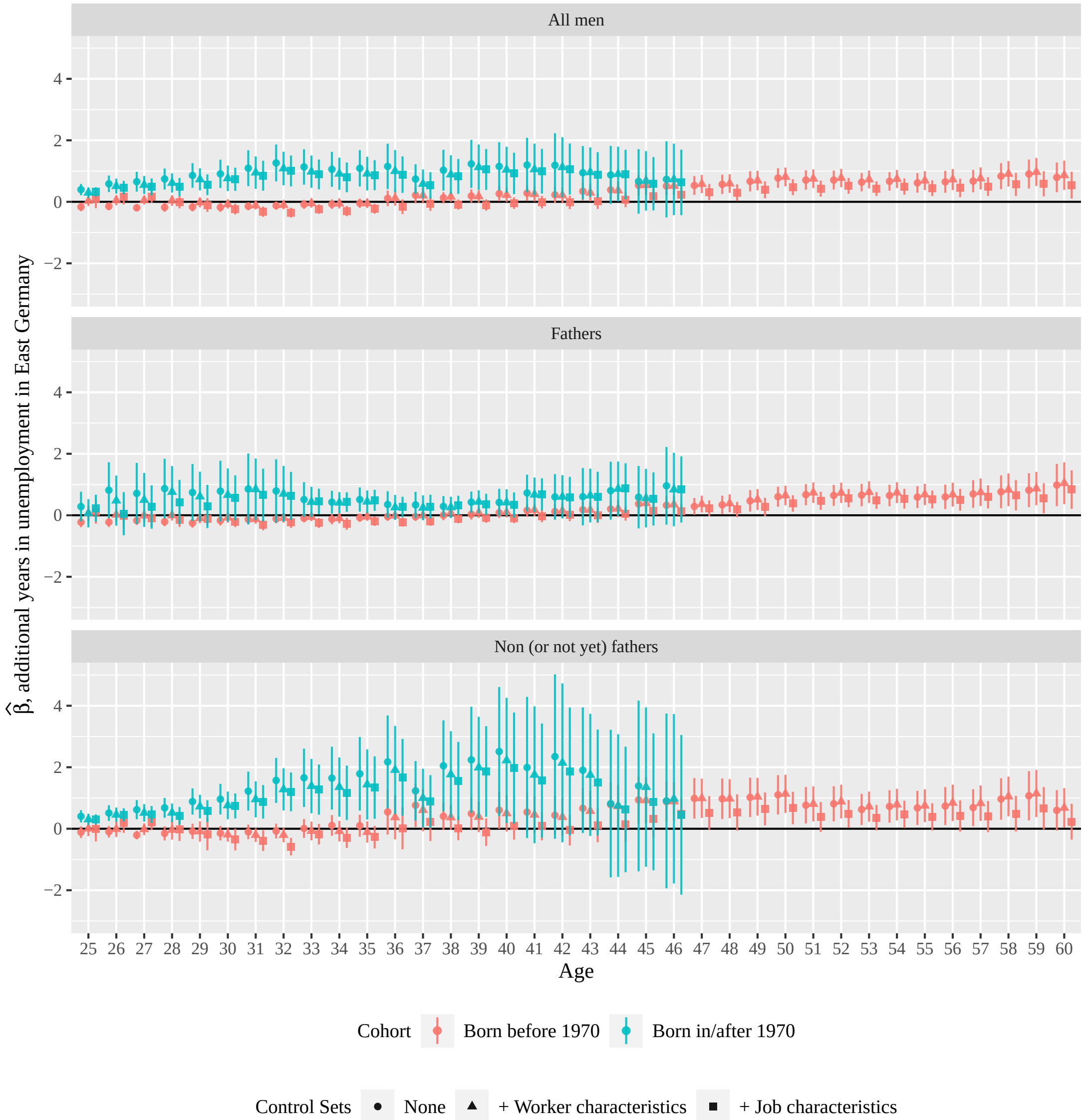
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in full-time experience as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate men born before 1970 (coral red) and men born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.9. Years of part-time experience, men by birth cohort.



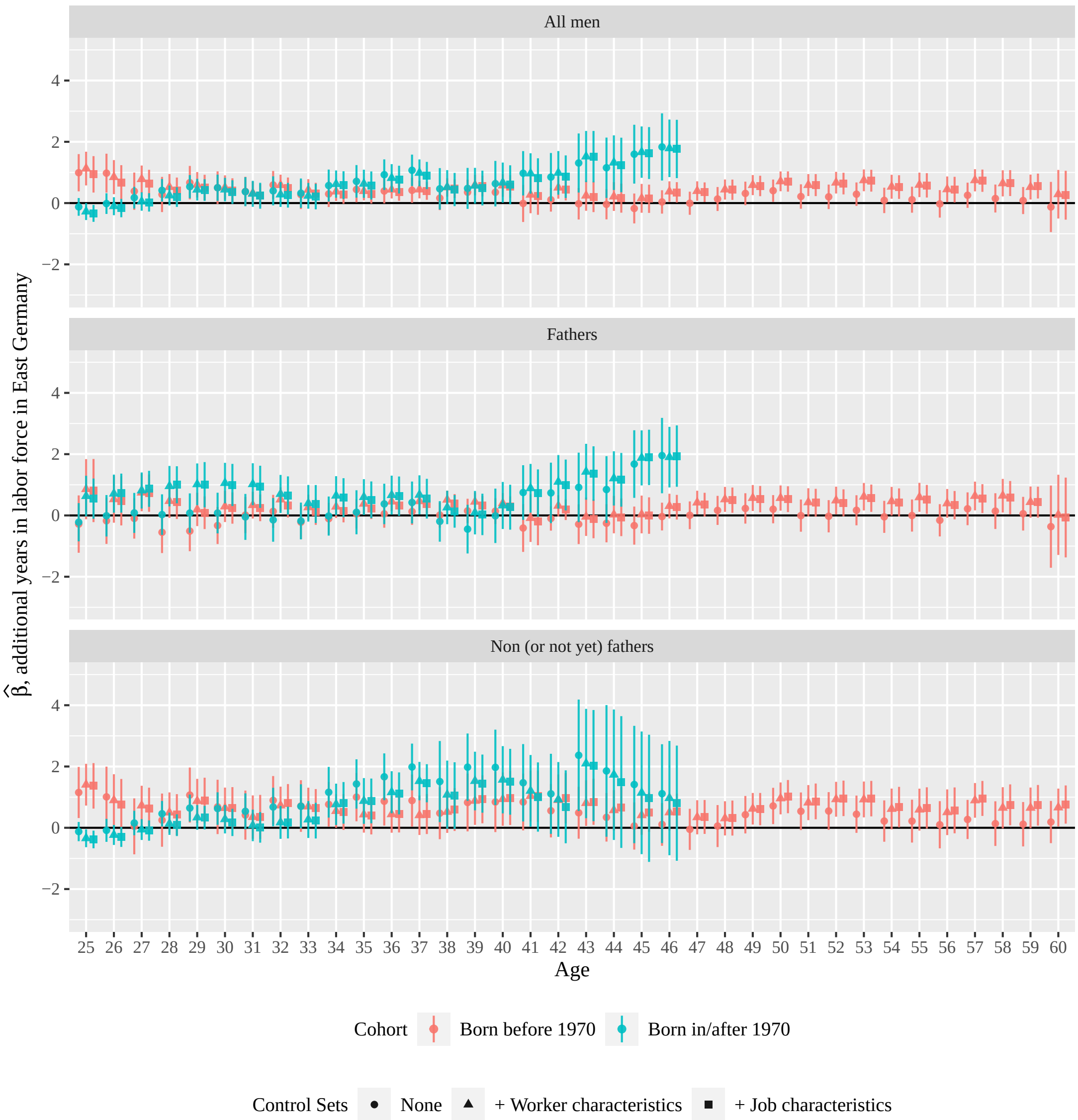
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years of part-time experience as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate men born before 1970 (coral red) and men born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.10. Years in unemployment experience, men by birth cohort.



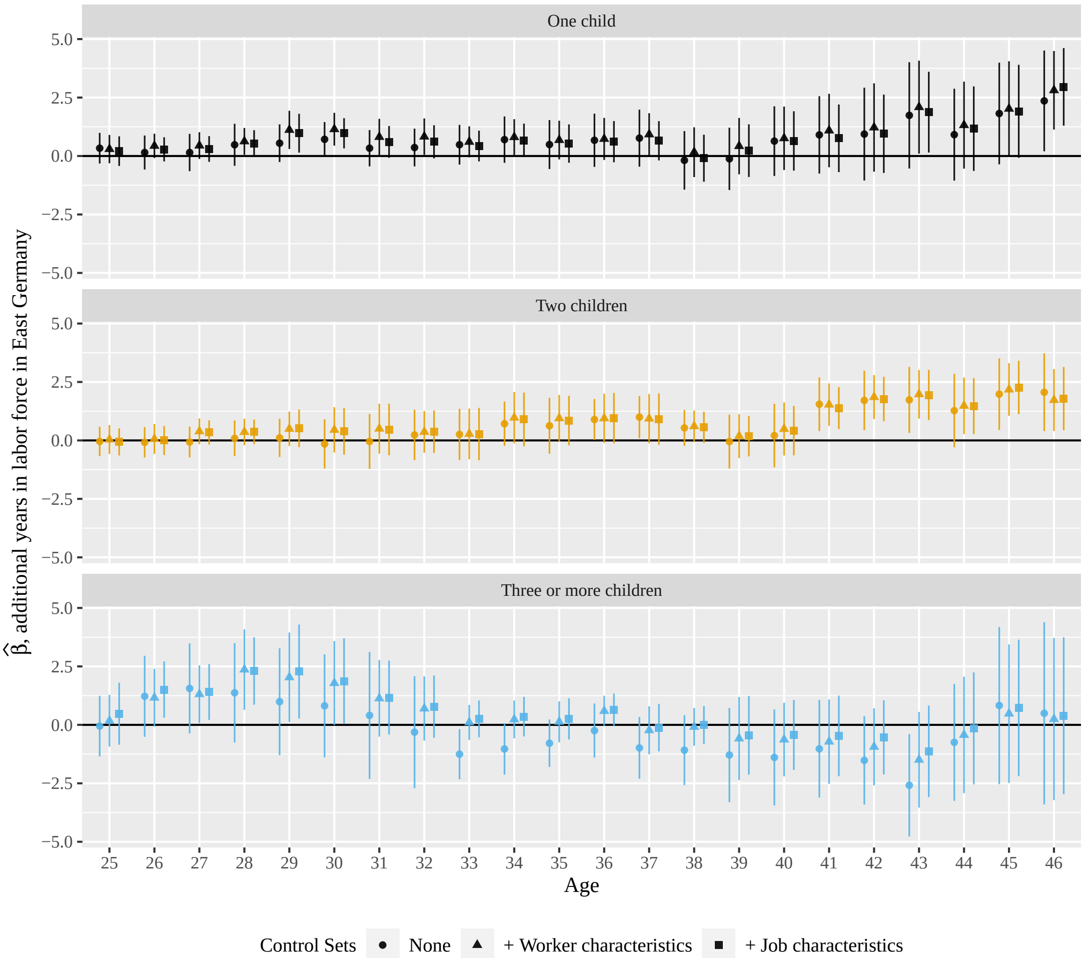
Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in unemployment as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate men born before 1970 (coral red) and men born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.11. Years in labor force, men by birth cohort.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. Colors indicate men born before 1970 (coral red) and men born in or after 1970 (turquoise). See the text for numbers of observations. Different sets of controls are indicated by point shape.

Figure 3.B.12. Years in labor force, men by number of children over the life cycle.



Notes: Dots are point estimates with 95% confidence intervals of $\widehat{\beta}_{gy}$ from equation (3.7), using years in labor force as dependent variable. Standard errors are heteroscedasticity robust. Sample of men born in or after 1970 who report a positive number of children over the life cycle (n = 31,763). The color indicates the number of children over the life cycle: one child (black, n = 9258), two children (yellow, n = 14,734) and three or more children (light blue, n = 7771).

4 Household Chores, Taxes, and the Labor-Supply Elasticities of Women and Men

4.1 Introduction

Women are often considered to supply market labor more elastically than men (e.g., Keane 2011). Alesina, Ichino, and Karabarbounis (2011) have worked out the optimal-tax implications of this observation: women should be taxed at lower marginal rates ("gender-based taxation"). They have also proposed a theoretical explanation for women's higher elasticities of market labor supply: the division of household chores between men and women. When women specialize more strongly in housework, they will supply *market* labor more elastically even when their underlying deep preferences are the same as those of men. Put differently, differences in market hours elasticities arise endogenously as a consequence of household specialization. These endogenous differences may be reinforced by gender differences in preferences which induce men and women to have different elasticities for a given division of household chores.

From an optimal-taxation perspective, it is important to assess quantitatively these two determinants of gender differences in labor-supply elasticities. Endogenous elasticity differences reflecting the division of household chores call for taxation based on roles within the household rather than gender, with the latter serving as an observable proxy. Yet, there are both proxy errors (those men who are very active in housework would erroneously be taxed at high rates as well) as well as the potential for better proxies (other variables observable to tax authorities may be more strongly correlated to roles in the household). By contrast, exogenous differences in preferences call for gender as a tax determinant in its own right rather than being just a proxy.

To investigate the roles of household specialization and preferences for labor-supply elasticities and the consequences for optimal taxation, we apply a model of joint decision making in dual-earner households regarding market labor supply and (unpaid) housework. The model incorporates the channel of elasticity differences due to the division of household chores as explored by Alesina, Ichino, and Karabarbounis (2011). Yet, unlike Alesina, Ichino, and Karabarbounis (2011), we allow for gender differences in preference parameters, facilitating a comparison of the two reasons for gender differences in labor-supply elasticities, the key driver for optimal marginal tax rates. As a second deviation from Alesina, Ichino, and Karabarbounis (2011), our model includes concave utility from consumption, which is important for estimating labor-supply elasticities (Altonji 1986; Domeij and Flodén 2006; Bredemeier, Gravert, and Juessen 2019; Bredemeier, Gravert, and Juessen 2023). This feature allows us to assess optimal tax rates quantitatively.

We use our model for two purposes. Firstly, we derive labor-supply conditions that can be estimated empirically and identify two different concepts of labor-supply elasticities: the Frisch elasticity of market labor supply and the elasticity of total labor supply, respectively, the latter being the sum of market and housework hours. Anticipating that women on average spend more time in housework relative to their market hours compared to men, the model predicts that women's elasticity of market labor supply is larger than men's, and that elasticities of total labor supply are both smaller than market elasticities and more similar across genders. Secondly, we use the model to determine the optimal relative marginal tax rates of the different members within a household. In line with the literature, we show that optimal relative marginal tax rates (inversely) reflect the relative elasticity of market labor supply and thus depend on exogenous preference parameters as well as the endogenous division of household chores.

In our empirical analysis, we use data from the Panel Study of Income Dynamics (PSID) to estimate the labor-supply conditions derived from our model. The results from these estimations serve to check the testable predictions of the model and as input into a subsequent quantitative optimal-taxation analysis. The results, firstly, confirm a significantly more elastic market labor supply of women. Secondly, they show that total hours respond less strongly to wage changes and in ways that are much more similar between genders. This speaks strongly in favor of the Alesina, Ichino, and

Karabarbounis (2011) housework channel, while our results also point to some role of gender beyond the division of household chores.

Finally, we assess quantitatively to what extent implementable tax rules can mimic optimal relative tax rates within households. Both in our model as in the Alesina, Ichino, and Karabarbounis (2011) model, optimal relative tax rates depend on the division of household chores. It is optimal to tax those household members at lower rates who work long housework hours. Yet, with housework time being difficult to observe and verify for the government, it seems impracticable to condition taxes on them. As the division of household chores is correlated with gender, gender-based taxation can raise tax efficiency through lowering marginal rates for women who are statistically more active in housework. We quantify how good a proxy gender can be for optimal relative tax rates and compare this to alternative tax rules using observables which are also correlated to the division of household chores such as household members' relative incomes or tags discussed in the literature such as body height. To this end, we use the results of our labor-supply regressions and data on market and housework hours from the PSID, to determine for every household in our data, the optimal relative marginal tax rates of its members implied by our model. We then perform accounting exercises as to how well simple tax rules that condition rates on observables such as gender or body height can proxy these optimal relative rates. Our results show that gender-based taxation can capture between 40% and 50% of the variation in optimal relative rates. To achieve these efficiency improvements, men's marginal tax rates would have to be 25 to 35 percentage points larger than women's. Gender-based taxation is dominated, however, by income-based tax rules that tax married spouses individually rather than jointly. Such rules can capture up to 60% of the variation in optimal tax rates. To mimic optimal within-couple tax rates as closely as possible, tax rates would rise in income with an elasticity of 0.4. This number is in the ballpark of the degrees of progressivity providing optimal levels of consumption insurance to married couples (Wu and Krueger 2021, Heathcote, Storesletten, and Violante 2017), while the empirical literature finds the current tax progressivity in the U.S. to be between 0.15 for married couples (Holter, Krüger, and Stepancuk 2023) and 0.21 for households with children (Heathcote, Storesletten, and Violante 2020). At the lower status-quo levels of tax progressivity, abolishing joint tax filing of married couples, which induces intra-household relative tax rates to depend on relative incomes, would already yield relative intra-household tax rates mimicking optimal relative tax rates to 40%.

The remainder of this paper is organized as follows. Section 4.2 discusses related literature. Section 4.3 presents the theoretical model and derives the estimation framework as well as optimal relative tax rates within households. Section 4.4 presents the empirical analysis and quantifies the accuracy of different implementable tax rules in mimicking optimal within-household tax rates. Section 4.5 concludes.

4.2 Related literature

The literature on using gender as a determinant of income tax rates can be divided into two classes: First, as initiated by Alesina, Ichino, and Karabarbounis (2011), gender-based taxation is proposed as a means of raising intra-household efficiency. This means that the amount of taxes collected from any household is not changed but the objective is to raise this amount more efficiently by shifting the tax burden between the incomes of household members. Hence, this literature does not focus on redistribution across households. Our paper belongs to this class of the literature.

Within this class, two arguments have been brought forward that counteract the Alesina, Ichino, and Karabarbounis (2011) channel. Hundsdoerfer and Matthaei (2020) point to the disadvantages of gender-based taxation stemming from its perceived unfairness and the resulting effects on labor supply. Meier and Rainer (2015) document a counteracting force arising from uninternalized externalities in non-cooperative couples. Raising one's labor earnings is beneficial to one's spouse which gives rise to a demand for Pigouvian subsidies in non-cooperative couples. The externality is more pronounced for the primary earner implying that this spouse should be taxed less (or subsidized more), counteracting the effect based on relative elasticities of labor supply which tends to call for lower tax rates on secondary earners' incomes. We add as another argument questioning the potential merits of gender-based taxation that there are alternative tax systems available that dominate gender-based taxation in terms of efficiency.

The second strand of the literature on gender-based taxation uses gender as a determinant in a redistributive tax rule. Due to the correlation between gender and income, taxing genders differently can redistribute income from rich to poor. Further, gender is not easily changed such that there is little to no tax evasion. Examples of quantitative assessments of gender-based redistributive taxation are Cremer, Gahvari, and Lozachmeur (2010) for the U.S. suggesting gains for low-wage workers, Berg (2023) for Norway, and Bastani (2013) for Sweden. Our paper is complementary to these studies as it considers tax efficiency within couples while their perspective is between individual agents of different gender.

Closely related to the intra-household efficiency of gender-based taxation is the literature on joint versus separate taxation. Boskin and Sheshinski (1983) have shown that the equal marginal tax rates that are levied on spouses under joint taxation are not optimal. By including home production in the analysis, Piggott and Whalley (1996) have pointed to a disadvantage of separate taxation as it distorts the specialization decisions of spouses into home production and market work, respectively. In response, Apps and Rees (1999) and Gottfried and Richter (1999) have shown that the Boskin and Sheshinski (1983) argument dominates the Piggott and Whalley (1996) argument in optimal tax systems, which always treat married spouses separately in deterministic settings. Introducing idiosyncratic income uncertainty, Corneo (2013) has demonstrated that in a stochastic model with exogenous labor supply, joint taxation provides higher consumption insurance than individual taxation. More recently, the literature has shifted toward quantitative assessments of tax systems, including the choice between separate and joint taxation of couples. Guner, Kaygusuz, and Ventura (2012) show in a quantitative model calibrated to the U.S. economy that moving from joint to separate taxation leads to strong increases in the labor supply of women, as well as higher welfare. Holter, Krüger, and Stepancuk (2023) find substantial welfare gains of a tax reform that combines a strong increase in tax progressivity and abolishing joint taxation in favor of separate taxation. Most of this literature points toward the efficiency gains associated with different marginal tax rates within the household, which is a deviation from joint taxation. Our results on the intra-household efficiency gains from separate taxation adds to this list.

Our paper is further related to the literature on estimating labor-supply elasticities, which we do to disentangle empirically the two determinants of gender differences in these elasticities and to obtain an input into our optimal-tax analysis. Keane (2011) surveys the literature on estimating male and female labor-supply elasticities. This literature is puzzled by the different magnitudes of labor supply elasticity estimates from micro and macro data, see Keane and Rogerson (2015) for a review. Numerous studies have contributed to bridging the gap between micro and macro estimates by revealing several downward biases in microeconometric estimates. For instance, Blomquist (1985, 1988), Alogoskoufis (1987), Heckman (1993), Rupert, Rogerson, and Wright (2000), Domeij and Flodén (2006), Faberman (2015), Bredemeier, Gravert, and Juessen (2019), and Bredemeier, Gravert, and Juessen (2023) have investigated potential downward biases in microeconometric estimates and have developed ways to correct for these biases. Elminejad et al. (2023) provides a meta-analysis of this literature. The estimation approach we apply in this paper takes into account these results and applies the proposed corrections.

4.3 Model

In this section, we present the theoretical model, derive labor-supply conditions for empirical estimation, and show the model's solution for optimal relative tax rates between spouses.

4.3.1 Model set-up

The model is populated by households, each consisting of a husband and a wife. Household j, which has members indexed by i, maximize the sum of its members' weighted expected life-time utility

$$U_j = E_0 \sum_{t=0}^{\infty} \beta^t v_{jt} = E_0 \sum_{t=0}^{\infty} \beta^t \sum_i \mu_{ijt} u_{ijt} \tag{4.1}$$

with period utility

$$u_{ijt} = v_{g(i),c}(c_{jt}) + v_{g(i),d}\,(d_{jt}) - \psi_{g(i)} \cdot \frac{l_{ijt}^{1+1/\eta_{g(i)}}}{1+1/\eta_{g(i)}}$$

where $g(i) = m, f$ gives individual i's gender, c is consumption of a bundle of market-produced goods and services, $v_c' > 0$, $v_c'' \leq 0$, d is consumption of home-produced goods and services, $v_d' > 0$, $v_d'' \leq 0$, and ψ_g and η_g are potentially gender-specific preference parameters. The weight μ_{ijt} assigned to individual i in period t reflects that member's bargaining power at that point in time, potentially depending on all time t state variables, such as wages and wealth.

Importantly, l_{ijt} measures *total* working time of member i and is the sum of hours of *market* work, n_{ijt}, and *housework* hours h_{ijt},

$$l_{ijt} = n_{ijt} + h_{ijt}.$$

These preferences nest the original Alesina, Ichino, and Karabarbounis (2011) preferences where both v_c and v_d are linear functions. For an empirical application, it is important to take into account variation in marginal utility (Altonji 1986, Domeij and Flodén 2006, Bredemeier, Gravert, and Juessen 2019, Bredemeier, Gravert, and Juessen 2023).

Households act subject to a budget constraint

$$c_{jt} + a_{jt+1} \leq \sum_i w_{ijt}^{net} n_{ijt} + (1 + r_t)\, a_{jt}, \tag{4.2}$$

where a is a risk-free asset, r its interest rate, and w^{net} are net (after-tax) wage rates, a housework production function

$$d_{jt} = f\left(\{h_{ijt}\}_i\right), \tag{4.3}$$

which is increasing and concave in both arguments, and a borrowing constraint

$$a_{jt+1} \geq a_t^{\min}, \tag{4.4}$$

where $a_{\min} \leq 0$ denotes (the negative of) a potentially age-dependent cap on borrowing. Wage rates are exogenous and evolve stochastically according to a process described by the probability density function $\omega(\{w_{ijt+1}^{net}\}_i | \{w_{ijt}^{net}\}_i)$.

With λ and λ^d denoting the Lagrange multipliers on the budget and housework constraints, (4.2) and (4.3), the first-order conditions to the household problem are[91]

$$\partial v_{jt} / \partial c_{jt} = \lambda_{jt}, \tag{4.5}$$

[91] Appendix 4.A.1 provides details.

$$\partial v_{jt}/\partial d_{jt} = \lambda^d_{jt}, \tag{4.6}$$

$$-\partial v_{jt}/\partial n_{ijt} = \lambda_{jt} w^{net}_{ijt} \ \forall\ i, \tag{4.7}$$

$$-\partial v_{jt}/\partial h_{ijt} = \lambda^d_{jt} \partial f/\partial h_{ijt} \ \forall\ i, \tag{4.8}$$

and an Euler equation that, next to the standard terms includes the multiplier on the borrowing constraint (4.2) and the potential response of future bargaining weights on accumulated wealth.

Combining the first-order conditions, we obtain the well-known results that the household balances the marginal rates of substitution between consumption and leisure to the net real wage rate and the marginal rate of substitution between market consumption and consumption of the housework good to their relative opportunity costs in terms of foregone leisure. We express these relations using upper-tier U as defined in (4.1), which is handy for the subsequent tax analysis,

$$\frac{\partial U_j}{\partial n_{ijt}} = -\frac{\partial U_j}{\partial c_{jt}} w^{net}_{ijt} \ \forall\ i, \tag{4.9}$$

$$\frac{\partial U_j}{\partial d_{jt}} = \frac{\partial U_j}{\partial c_{jt}} \frac{w^{net}_{ijt}}{\partial f/\partial h_{ijt}} \ \forall\ i. \tag{4.10}$$

Frisch elasticities and labor-supply regressions. The first-order condition for market labor supply n_{ijt}, (4.7), can be used to derive Frisch elasticities and labor-supply conditions that can be estimated in linear regressions. Applying the functional form of labor disutility yields

$$\mu_{ijt}\psi_{g(i)} \cdot l^{1/\eta_i}_{ijt} = \lambda_{jt} w^{net}_{ijt}.$$

A first-order approximation in logs gives

$$\widehat{l}_{ijt} = \eta_{g(i)} \widehat{w}^{net}_{ijt} + \eta_{g(i)} \widehat{\lambda}_{jt} - \eta_{g(i)} \widehat{\mu}_{ijt}, \tag{4.11}$$

where, for a generic variable $x = l,\, n,\, h,\, \lambda,\, w$, $\widehat{x} = \log(x/\overline{x})$ and $\overline{x}$ is the point of approximation.[92] This condition shows that the *Frisch elasticity of total work* l_i is simply given by the preference parameter $\eta_{g(i)}$. If there are no gender differences in this parameter, this elasticity is identical for men and women.

[92] Appendix 4.A.3 provides details.

To derive the elasticity of *market labor supply*, first use the definition $l_{ijt} = n_{ijt} + h_{ijt}$ to log-linearize, with $\widehat{x} = \log(x/\overline{x}) \approx \frac{x-\bar{x}}{\bar{x}}$

$$\widehat{l}_{ijt} = \frac{\overline{n}_{ij}}{\overline{l}_{ij}}\widehat{n}_{ijt} + \frac{\overline{h}_{ij}}{\overline{l}_{ij}}\widehat{h}_{ijt}. \tag{4.12}$$

Then combine (4.11) and (4.12) and solve for market hours $\widehat{n}_{ijt}$ to obtain

$$\widehat{n}_{ijt} = \frac{\overline{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{w}^{net}_{ijt} - \frac{\overline{h}_{ij}}{\overline{n}_{ij}}\widehat{h}_{ijt} + \frac{\overline{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{\lambda}_t - \frac{\overline{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{\mu}_{ijt}. \tag{4.13}$$

The *Frisch elasticity of market work* n_i is given by

$$e^{Frisch}_{ijt} = \frac{\partial \widehat{n}_{ijt}}{\partial \widehat{w}^{net}_{ijt}}|_{\lambda,\mu} = \frac{\overline{l}_{ij}}{\overline{n}_{ij}} \cdot \eta_{g(i)} - \frac{\overline{h}_{ij}}{\overline{n}_{ij}} \cdot \frac{\partial \widehat{h}_{ijt}}{\partial \widehat{w}^{net}_{ijt}}|_{\lambda,\mu} \approx \frac{\overline{l}_{ij}}{\overline{n}_{ij}} \cdot \eta_{g(i)}. \tag{4.14}$$

The additional term $\overline{h}_{ij}/\overline{n}_{ij} \cdot \partial\widehat{h}_{ij}/\partial\widehat{w}_{ij}|_{\lambda,\mu}$ has no substantial influence on the market hours elasticity as shown by Bredemeier, Gravert, and Juessen (2023). There remain two main reasons for gender differences in the Frisch elasticity of market work. First, when men and women divide their total working time l to market work and housework in different proportions, as, e.g., in the Alesina, Ichino, and Karabarbounis (2011) model. On average, women will tend to have higher Frisch elasticities of market work because the average value of $\overline{l}_{ij}/\overline{n}_{ij}$ is higher for women. Second, gender differences in Frisch elasticities may result from men and women differing in the preference parameter η_i.

Empirical applications have to deal with the fact that the labor-supply conditions (4.11) and (4.13) include two not directly observable elements, the marginal utility $\widehat{\lambda}_{jt}$ and the bargaining weight $\widehat{\mu}_{ijt}$. To address these challenges, we follow Bredemeier, Gravert, and Juessen (2023) who show that these variables can be expressed as log-linear functions of the household's consumption expenditures $\widetilde{c}_{jt}$ and the share it spends on a category of consumption goods k, $\widetilde{c}_{kjt}/\widetilde{c}_{jt}$, respectively, plus an approximation error. Using this result, the labor-supply conditions (4.11) and (4.13) can be rewritten into the following regression equations:

$$\log n_{ijt} = \kappa^n_i + \frac{\overline{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)} \log w^{net}_{ijt} - \frac{\overline{h}_{ij}}{\overline{n}_{ij}} \log h_{ijt} + \alpha^n_{g(i)} \log \widetilde{c}_{jt} + \gamma^n_{g(i)} \log\left(\frac{\widetilde{c}_{kjt}}{\widetilde{c}_{jt}}\right) + \varepsilon^n_{ijt} \tag{4.15}$$

and

$$\log l_{ijt} = \kappa_i^l + \eta_{g(i)} \log w_{ijt}^{net} + \alpha_{g(i)}^l \log \widetilde{c}_{jt} + \gamma_{g(i)}^l \log \left(\frac{\widetilde{c}_{kjt}}{\widetilde{c}_{jt}} \right) + \varepsilon_{ijt}^l, \tag{4.16}$$

where the individual fixed effects κ^n and κ^l collect the long-run averages of the included variables, ε^n and ε^l are residuals reflecting approximation errors as well as measurement error, and the parameters α^n, γ^n, α^l, and γ^l combine the proxy relations discussed above with the slope coefficients from (4.11) and (4.13).

In our empirical analysis, we will estimate (4.15) and (4.16) separately for men and women. Thus, for each gender, we run, first, a regression with log market hours as the dependent variable and then a regression with log total hours as the dependent variable. In both types of regressions, the log wage rate is the main independent variable. All regressions further include individual fixed effects and the appropriate controls and a constant. The market-hours regression additionally includes log housework hours on the right-hand side.

Anticipating that the terms $\overline{l}_{ij}/\overline{n}_{ij}$ and $\overline{h}_{ij}/\overline{n}_{ij}$ are, on average, larger for women than for men, we can formulate the following conjectures implied by the model for the results of such regressions. Unless offset by a strong counteracting difference in the preference parameters, i.e. $\eta_m \gg \eta_f$, we expect that firstly, the coefficient on the wage rate in the market-hours regression (4.15) is larger for women, and, secondly, the coefficients on the wage rate in the total-hours regression (4.16) are more similar between men and women than the corresponding coefficients in the market-hours regression (4.15). Importantly, the results of the total-hours regression identify the preference parameters η_g, which we use in the empirical analysis of optimal tax rates.

4.3.2 Optimal taxation

We now discuss the model's normative implications for income tax rates. Specifically, we show how the government should tax the individual members of a household relative to one another. Our aim is to derive a simple expression that summarizes this implication in terms of objects that can be observed or estimated empirically.

We abstract from redistributive aspects of taxation and take as given the amount of taxes G_j the government wants to collect from household j using labor income taxes.

We consider how to collect this amount in the most efficient way. Further, we concentrate on a structural perspective, i.e., how to tax spouses in general, independent of occasionally binding borrowing constraints and potential changes in intra-household bargaining power. When deciding on tax rates for the two members of household j at a given period of time, the government maximizes household utility U_j as defined in (4.1) and described by the first-order conditions (4.5) to (4.8) subject to

$$\sum_i \tau_{ijt} w_{ijt} n_{ijt} = G_{jt}, \tag{4.17}$$

where w denote gross (before-government) wage rates and τ are tax rates to be set optimally.

The first-order condition for tax rate τ_{ijt} is

$$\begin{aligned} &\frac{\partial U_j}{\partial c_{jt}} \cdot \frac{\partial c_{jt}}{\partial \tau_{ijt}} + \frac{\partial U_j}{\partial d_{jt}} \cdot \frac{\partial d_{jt}}{\partial \tau_{ijt}} + \frac{\partial U_j}{\partial h_{ijt}} \cdot \frac{\partial h_{ijt}}{\partial \tau_{ijt}} + \frac{\partial U_j}{\partial h_{-ijt}} \cdot \frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \\ &\quad + \frac{\partial U_j}{\partial n_{ijt}} \cdot \frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \frac{\partial U_j}{\partial n_{-ijt}} \cdot \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \\ &\quad + \lambda^G_{jt} \cdot \left(w_{ijt} n_{ijt} + \tau_{ijt} w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \tau_{-ijt} w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \right) = 0, \end{aligned} \tag{4.18}$$

where λ^G_{jt} is the Lagrange multiplier on (4.17) and $-i$ indicates the partner of individual i. This condition simplifies considerably when first-order conditions and constraints of the household problem are substituted. Specifically, using the optimality conditions (4.9) as well as (4.10) and the constraints (4.2) with $a_{jt+1} = (1+r)a_{jt}$ and (4.3) gives, after collecting terms,

$$-\frac{\partial U_j}{\partial c_{jt}} + \lambda^G_{jt} \cdot \left(1 + \frac{\partial n_{ijt}}{\partial \tau_{ijt}} \frac{\tau_{ijt}}{n_{ijt}} + \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \frac{\tau_{-ijt} w_{-ijt}}{w_{ijt} n_{ijt}} \right) = 0, \tag{4.19}$$

see Appendix 4.A.2 for a detailed derivation.

For not too large values of τ_{ijt}, $\partial x / \partial \tau_{ijt} \approx -\frac{\partial x}{\partial w_{ijt}} w_{ijt}$ for any variable x, because both an absolute increase in τ and a relative decrease in the gross wage rate by the same amount induce the same change in the decision relevant net wage rate. Defining

$$e^{own}_{ijt} = \frac{\partial n_{ijt}}{\partial w_{ijt}} \cdot \frac{w_{ijt}}{n_{ijt}},$$

$$e_{ijt}^{cross} = \frac{\partial n_{ijt}}{\partial w_{-ijt}} \cdot \frac{w_{ijt}}{n_{-ijt}},$$

we can simplify (4.18) to

$$-\frac{\partial U_j}{\partial c_{jt}} + \lambda_{jt}^G \cdot \left(1 + \tau_{ijt} e_{ijt}^{own} + \tau_{-ijt} e_{-ijt}^{cross}\right) = 0, \tag{4.20}$$

which needs to hold for both i and $-i$, hence describing a system of two equations in two unknowns, τ_{ijt} and τ_{-ijt}. This system can be solved for the ratio of optimal tax rates within the household,

$$\frac{\tau_{ijt}^*}{\tau_{-ijt}^*} = \frac{e_{-ijt}^{own} - e_{-ijt}^{cross}}{e_{ijt}^{own} - e_{ijt}^{cross}}. \tag{4.21}$$

This is an application of Ramsey's inverse-elasticity rule. The tax rate which induces smaller behavioral responses should be set higher. In general, these responses include the reaction to changes in one's tax rate on the partner's labor supply.

Note that e_{ijt}^{cross} is not exactly the cross-wage elasticity as it is usually defined but multiplies the cross-wage derivative with the ratio of one's own wage to one's partner's hours. The term thus measures by how much hours of one partner respond (in percent of his/her partner's hours) to a change in his/her partner's wage rate (in percent of one's own wage). This is important because it implies that the income effects included in the two derivatives cancel when the derivatives are subtracted from one another.

As shown by Chaudhuri (1995), $\partial n_{ijt}/\partial w_{ijt}$ and $\partial n_{ijt}/\partial w_{-ijt}$ can be decomposed into

$$\frac{\partial n_{ijt}}{\partial w_{ijt}} = \frac{\partial n_{ijt}}{\partial w_{ijt}}|_{\lambda} + n_{ijt}\frac{\partial n_{ijt}}{\partial y_{jt}} - \xi_{ijt}^{own},$$
$$\frac{\partial n_{ijt}}{\partial w_{-ijt}} = \frac{\partial n_{-ijt}}{\partial w_{ijt}}|_{\lambda} + n_{-ijt}\frac{\partial n_{ijt}}{\partial y_{jt}} - \xi_{ijt}^{cross},$$

where y_{jt} is the period-t value of household j's stream of unearned income. The first term is the derivative of the Frisch labor-supply function, the second term is the classical income effect known from textbook Slutsky decompositions and the final term is the general substitution effect (Houthakker 1960). The general substitution effect captures the changes in income in response to behavioral changes, specifically the changes in all supply and demand decisions according to the respective Frisch supply or demand functions.

In our case with additively separable preferences, the only Frisch responses are with respect to the decision variable's own price. That implies

$$\xi_{ijt}^{own} = \frac{\partial n_{ijt}}{\partial y_{jt}} w_{ijt} \frac{\partial n_{ijt}}{\partial w_{ijt}}|_\lambda,$$
$$\xi_{ijt}^{cross} = \frac{\partial n_{ijt}}{\partial y_{jt}} w_{-ijt} \frac{\partial n_{-ijt}}{\partial w_{-ijt}}|_\lambda.$$

Further, additively separable preferences imply that the Frisch cross-wage derivative in $\partial n_{ijt}/\partial w_{-ijt}$ is zero. Consequently, the difference between the own-wage and the cross-wage elasticities in (4.21) simplifies to

$$\begin{aligned}
e_{ijt}^{own} - e_{ijt}^{cross} &= \frac{\partial n_{ijt}}{\partial w_{ijt}} \cdot \frac{w_{ijt}}{n_{ijt}} - \frac{\partial n_{ijt}}{\partial w_{-ijt}} \cdot \frac{w_{ijt}}{n_{-ijt}} \\
&= \left(\frac{\partial n_{ijt}}{\partial w_{ijt}}|_\lambda + n_{ijt} \frac{\partial n_{ijt}}{\partial y_{jt}} \right) \cdot \frac{w_{ijt}}{n_{ijt}} - n_{-ijt} \frac{\partial n_{ijt}}{\partial y_{jt}} \cdot \frac{w_{ijt}}{n_{-ijt}} \\
&\quad - \xi_{ijt}^{own} \cdot \frac{w_{ijt}}{n_{ijt}} + \xi_{ijt}^{cross} \cdot \frac{w_{ijt}}{n_{-ijt}} \\
&= e_{ijt}^{Frisch} - \frac{\partial n_{ijt}}{\partial y_{jt}} \cdot w_{ijt} \cdot \left(e_{ijt}^{Frisch} - e_{-ijt}^{Frisch} \right)
\end{aligned}$$

and the analogous steps for $e_{-ijt}^{own} - e_{-ijt}^{cross}$ give

$$e_{-ijt}^{own} - e_{-ijt}^{cross} = e_{-ijt}^{Frisch} - \frac{\partial n_{-ijt}}{\partial y_{jt}} \cdot w_{-ijt} \cdot \left(e_{-ijt}^{Frisch} - e_{ijt}^{Frisch} \right)$$

Thus, optimal relative marginal tax rates depend on (Frisch) substitution effects while income effects cancel out. Further notice that the latter term tends to be small when the two household members' Frisch elasticities are not too different.

To simplify terms further, we apply a first-order Taylor approximation of $e_{ijt}^{own} - e_{ijt}^{cross}$ around the situation where spouses are identical in all respects, implying for example equal Frisch elasticities. This gives, in logs,

$$\log(e_{ijt}^{own} - e_{ijt}^{cross}) \approx (1-\gamma) \log e_{ijt}^{Frisch} + \gamma \log e_{-ijt}^{Frisch},$$

with $\gamma = w \cdot \partial n / \partial y$ is the (individual) propensity to earn out of (family) unearned income in the point of approximation where no individual indices are needed due to symmetry. Using the approximation, we can write

$$\begin{aligned}
&\log(e_{ijt}^{own} - e_{ijt}^{cross}) - \log(e_{-ijt}^{own} - e_{-ijt}^{cross}) \\
&\qquad \approx (1-\gamma)\log e_{ijt}^{Frisch} + \gamma \log e_{-ijt}^{Frisch} - (1-\gamma)\log e_{-ijt}^{Frisch} - \gamma \log e_{ijt}^{Frisch} \\
&\qquad = (1-2\gamma)\log e_{ijt}^{Frisch} - (1-2\gamma)\log e_{-ijt}^{Frisch}.
\end{aligned}$$

Thus, the log ratio of optimal marginal tax rates in a household satisfies

$$\log\left(\tau_{ijt}^{*}/\tau_{-ijt}^{*}\right) \approx (1-2\gamma)\left(\log e_{-ijt}^{Frisch} - \log e_{ijt}^{Frisch}\right). \tag{4.22}$$

As wealth effects cancel, optimal relative tax rates depend on substitution effects alone, measured by Frisch elasticities. The slope $1-2\gamma$ contains the family's propensity to earn out of (family) unearned income, 2γ. As γ is negative, but empirical estimates are mostly modest, the slope is a number larger than one but likely not larger than 1.5. We review the empirical literature on the marginal propensity to earn out of unearned income in Appendix 4.B.

Independent of the particular value of 2γ, the optimal tax rate ratio includes the difference between spouses' Frisch elasticities. The government would optimally tax that spouse at a higher rate whose Frisch labor supply is less elastic. In our model, differences in Frisch elasticities can stem from differences in preferences, which might be gender specific, and from differences in time use with individuals that work more in housework activities having larger Frisch elasticities. The model thus has room for both gender-based taxation and for taxation based on the division of household chores. Which of the two dominates the other and how tax codes can be constructed to mimic optimal intra-household marginal tax rates is an empirical question that we address in the subsequent section.

4.4 Empirical Analysis

In this section, we quantify how well different tax rules, including gender-based taxation, can mimic optimal relative marginal tax rates within couples, as implied by the theoretical model. For this, we first estimate the preference parameter η_g, which measures the Frisch elasticity of total hours worked. We then use these estimates and observable information on home and market hours to predict optimal relative marginal tax rates within couples. In the final step, we run regressions with these predicted optimal relative tax rates as dependent variables and observables upon which tax rates may be conditioned, such as gender or income, as independent variables. These regressions inform us about how strongly marginal tax rates should depend on these observables as well as about how well the resulting tax rules could mimic intra-household tax efficiency.

4.4.1 Variable definitions

Data and sample selection. We use (biennial) waves 1999-2021 of the Panel Study of Income Dynamics (PSID). Bredemeier, Gravert, and Juessen (2023) have shown how the available data on household consumption in these recent waves of the PSID can be used to estimate labor-supply elasticities.[93] Our sample selection closely follows their paper (also see Blundell, Pistaferri, and Saporta-Eksten 2016).

We consider married heterosexual couple households where both spouses are between 25 and 60 years old. We exclude the Survey of Economic Opportunity sample and the immigrant sample, drop observations with wages below half the hourly minimum wage, observations where couples report very high asset values ($20 million and more), couples who receive transfers higher than twice total household earnings and we do not use data displaying extreme jumps from one PSID wave to the next, see Blundell, Pistaferri, and Saporta-Eksten (2016) for details. Our sample consists of stable couples, which means that we drop couples in the period where they dissolve but include these household heads when they marry again and consider them and their new partner as a new couple. Throughout, we use PSID sampling weights.

Market hours, housework, and wages. The market hours variable is annual hours worked, calculated as weeks worked times usual weekly hours plus overtime hours. The PSID provides a housework variable which covers cooking, cleaning, and other work

[93] Their approach corrects both for the bias due to occasionally binding borrowing constraints (extending the seminal approach by Altonji 1986) and for the bias due to limited commitment in the household.

around the house.[94] We treat missing values in the housework variable as zeros and add a one to this variable before including it as logged variable in the regressions.

The hourly wage rate is calculated by dividing annual earnings by annual hours of market work. By construction, this leads to the well-known division bias in regressions with hours worked and hourly wages. We will account for this in our analysis. Annual earnings are measured in real (year 2000) dollars and consist of labor earnings, the labor part of business income, and the labor part of farm income. As pointed out by Blomquist (1985, 1988), it is crucial to use net wage rates rather than gross wage rates in labor-supply regressions. To convert gross wages into net wages, we compute taxes and determine eligible amounts of Earned Income Tax Credit (EITC) and food stamps benefits based on program information for the included survey years. Our computation factors in the variations in benefits on demographic characteristics such as the number and age of children. We determine marginal tax rates by calculating the change in income after taxes and transfers induced by a $500 increase in gross annual earnings. The net wage rate is then obtained by multiplying the gross wage rate by one minus the marginal tax rate.

Additional variables. The approach for estimating labor-supply elasticities developed by Bredemeier, Gravert, and Juessen (2023) uses expenditure variables to account for the distribution of household consumption as a proxy for relative household bargaining power. We follow their preferred implementation and include in the labor-supply regressions the expenditure share for food, next to total household consumption. Total household consumption is defined as the sum of expenditures on the individual consumption items.

Our labor-supply regressions further include individual and time fixed effects. Individual fixed effects capture heterogeneity in the taste for work and differences in other unobserved characteristics across individuals. Time effects are included to eliminate both price effects and effects related to the business cycle, e.g., demand-driven economy-wide factors. To account for taste shifters that display time variation, we include a third-order polynomial in age and the number of young (below age 7) and old (age 7-17) children in the household. Other variables affecting the taste for work

[94] Shopping and caring for children or adult family members needing assistance are addressed in separate questions but only since 2017.

which are mostly constant over time, such as education, are effectively accounted for by individual fixed effects.

Wage regression. Labor-supply regressions are subject to a division bias when wage rates have to be computed as earnings divided by hours worked, see, e.g., Altonji (1986), Borjas (1980), Pencavel (1986), and Keane (2011). This generates a spurious negative correlation of the calculated wage rate with hours worked because measurement error in hours worked occurs on both sides of the regression equation. As in Bredemeier, Gravert, and Juessen (2023), we therefore run an initial wage regression, separately for men and women, and use it to determine predicted wage rates which are uncorrelated with the measurement error in hours worked. We then use predicted log (net) wage rates $\log \widetilde{w}_{ijt}$ in the labor-supply regressions.

Next to being uncorrelated to the measurement error in hours, variables on the right-hand side of the wage regession should be uncorrelated to idiosyncratic shocks to the taste for work. Thereby, the predicted wage variation reflects variation in labor *demand*, due to, e.g., changes in productivity or business conditions, which allows the identification of the slope of the labor *supply* curve, i.e., the elasticity of labor supply.

We consider different specifications of the wage regression to test for robustness. Our baseline specification is very similar to the one used in Bredemeier, Gravert, and Juessen (2023). The key idea is to exploit education-specific life-cycle patterns in wages. Specifically, we include a third-order polynomial in age and interactions of these terms with education, firm tenure, firm tenure squared, state dummies, year dummies, and, following Altonji (1986), the other variables from the labor-supply regression, as well as individual fixed effects. In an alternative specification, we consider a broader set of wage predictors. In particular, in the spirit of a Bartik (shift-share) approach, we include an interaction between the individual's industry and the national rate of unemployment (in the previous year), and, following Attanasio et al. (2018), 10-year birth cohorts interacted with education and a quintic time trend. We also investigate whether our results change substantially when we account for wives' selection into the labor market.

Table 4.1. Market hours and total hours regressions.

	(1)	(2)	(3)	(4)
	log market hours, $\log n_{ijt}$		log total hours, $\log l_{ijt}$	
	men	women	men	women
log wage rate, $\log w_{ijt}$	0.602***	1.133***	0.380***	0.449***
	(0.046)	(0.082)	(0.034)	(0.042)
log housework, $\log h_{ijt}$	-0.0415***	-0.141***		
	(0.0049)	(0.010)		
Observations	17516	17516	17516	17516

Notes: Dependent variables are log hours worked in the market, $\log n_{ijt}$ (columns (1) and (2)), and log total hours worked, $\log l_{ijt}$ (columns (3) and (4)). All regressions include individual and time fixed effects, taste shifters (number of young kids, number of old kids, cubic in age), log household consumption, log share of food expenditures, and a constant. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.4.2 Labor-supply elasticities

Our sample consists of couples where both, husband and wife work for pay, which by construction yields samples for men and women that are of equal size. We begin with estimating the market-hours regression (4.15), hence we regress (log) market hours on (log) predicted (net) wage rates, (log) housework time, individual and time fixed effects, as well as taste shifters. In addition, we include (log) household total consumption and the expenditure share on food. Thereafter, we will estimate the corresponding regression for total hours.

The first two columns in Table 4.1 show the results for market hours. For men, the estimated wage elasticity is 0.60 which is similar to the numbers for men reported in Bredemeier, Gravert, and Juessen (2023). The estimate for women is 1.13 and hence almost twice as large. Thus, as expected, the estimates for the Frisch elasticity of market work are substantially larger for women than for men.

Columns (3) and (4) in Table 4.1 show the results for the total-hours regression, with log total hours as the dependent variable and the log wage rate as the main independent variable, see (4.16). As discussed before, the conjecture is that the coefficients on the wage rate in this regression are more similar between men and women than in the market-hours regression shown in columns (1) and (2). The empirical results are in line with this conjecture. The estimated total-hours elasticity for men is 0.38 and the one for women is 0.449. Compared to the pronounced gender differences in the market-hours elasticity, these differences are rather small. Taken together, the results reported in Table 4.1 are in line with the Alesina, Ichino, and Karabarbounis (2011) channel as well as with the particular assumptions of their model. In their model, it is assumed that there are no deep gender differences in preferences, i.e., the wage elasticities of total time are assumed to be identical, and differences in market-hours elasticities between men and women arise endogenously due to household decisions, with women having the higher elasticity of market hours to wages on average.

Couples without young children. It is interesting to reconsider our previous estimates in a restricted sample of couples where there are no young kids living in the household. One would expect that the Alesina, Ichino, and Karabarbounis (2011) channel of household specialization is less relevant in a sample of households where there is less scope for household specialization. Hence, we would expect smaller gender differences in market-hours elasticities in this evaluation compared to the numbers reported in columns (1) and (2) of Table 4.1. In the restricted sample, the estimated market-hours elasticities are 0.633 for men and 0.93 for women, and are hence, as expected, more similar than in the full sample.[95] Consequently, the large gender differences in the elasticities of market labor supply are primarily driven by mothers of young children, who can be expected to work long home hours relative to their market hours.

Robustness. To investigate the robustness of our key findings regarding the strength of gender differences in different elasticity concepts, we reestimate our regressions using a broader set of regressors when predicting wage rates. In the spirit of a Bartik (shift-share) approach, we add to the wage regression an interaction between the individual's industry and the national rate of unemployment (in the previous year). In addition, we include 10-year birth cohorts interacted with education and a quintic time trend, as suggested by Attanasio et al. (2018). Table 4.2 shows the results for the labor-supply regressions when wage rates are predicted using this alternative approach. While estimated elasticities are smaller than in our baseline specification, also this evaluation confirms that gender differences in total-hours elasticities (and hence gender differences in preferences) are substantially smaller than gender differences in market-hours elastic-

[95] Detailed results can be found in Appendix 4.C, Table 4.C.1.

Table 4.2. Market hours and total hours regressions, broader set of wage predictors.

	(1)	(2)	(3)	(4)
	log market hours, $\log n_{ijt}$		log total hours, $\log l_{ijt}$	
	men	women	men	women
log wage rate, $\log w_{ijt}$	0.379***	0.673***	0.225***	0.283***
	(0.038)	(0.058)	(0.028)	(0.030)
log housework, $\log h_{ijt}$	-0.0416***	-0.143***		
	(0.0049)	(0.010)		
Observations	17516	17516	17516	17516

Notes: Dependent variables are log hours worked in the market, $\log n_{ijt}$ (columns (1) and (2)), and log total hours worked, $\log l_{ijt}$ (columns (3) and (4)). All regressions include individual and time fixed effects, taste shifters (number of young kids, number of old kids, cubic in age), log household consumption, log share of food expenditures, and a constant. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ities. As shown in Section 4.3, model-implied optimal tax rates depend on the *relative* difference between gender-specific total-hours elasticities while the absolute levels of these elasticities do not play an important role. Estimated relative elasticities are remarkably similar across specifications, with women's total-hours elasticity exceeding men's by a factor between 1.18 (Table 4.1) and 1.25 (Table 4.2). For market hours, the ratios of estimates are 1.78 (Table 4.2) and 1.88 (Table 4.1) and hence substantially larger.

Selection. While married men 25-65 years old have a participation rate of 93% in our sample, the participation rate for married women is smaller (81%). To investigate the role of women's selection into work for our results, we estimate a discrete-choice model for female participation to calculate an inverse Mills ratio which is then included on the right-hand side in the female wage equation as an additional regressor. We follow Blundell, Pistaferri, and Saporta-Eksten (2016) and Del Boca and Lusardi (2003) in the choice of instruments, the latter study providing evidence that female participation rises when households move into home ownership. They therefore suggest as instruments the presence of first and second mortgages interacted with year dummies. Table 4.C.2 in the Appendix shows the results obtained when we predict wages using our baseline set of regressors but additionally control for selection effects. In line with the literature, see, e.g. Blundell, Pistaferri, and Saporta-Eksten (2016), we find that the correction for selection makes little difference.

4.4.3 Intra-household efficiency of alternative tax rules

We now analyze how well tax rules such as gender-based taxation can mimic optimal relative intra-household tax rates as implied by our model. Recall that our model implies that optimal relative marginal tax rates in a household are given by (4.22), which, with Frisch elasticities (4.14) substituted in, reads

$$\theta^*_{ijt} = \log(\tau^*_{ijt}/\tau^*_{-ijt}) = (1-2\gamma)\left(-\log \eta_{g(i)} + \log \eta_{g(-i)} \right. \\ \left. + \log(\overline{n}_{ij}/\overline{l}_{ij}) - \log(\overline{n}_{-ij}/\overline{l}_{-ij})\right). \tag{4.23}$$

We use this equation to determine for every individual in our sample an implied optimal relative tax rate. We then run regressions with θ^*_{ijt} as the dependent variable and potential elements of a tax rule (income, gender, other tags) as independent variables. The R^2 statistics of these regressions measure how well a tax rule with the respective set of determinants mimics intra-household tax efficiency. The estimated coefficients inform us about how strongly tax rate should be conditioned on the respective observable from an intra-household efficiency perspective.

We take gender-specific Frisch elasticities of total working time from our estimates presented in the previous section. As a baseline, we use the estimates from columns (3) and (4) of Table 4.1 for η_m and η_f. Information on market hours n and total hours $l = n+h$ are directly taken from the PSID. Regarding the multiplicative constant $1-2\gamma$, the literature suggests that it lies between 1 and 1.5, see Section 4.3. Yet, its exact value is of secondary importance for our analysis as it simply scales up or down the estimated coefficients with no effect on the R^2, our main measure of interest. We therefore choose, for simplicity, the lower bound of $1-2\gamma = 1$, being aware that coefficients may be scaled up by up to 50% for other reasonable values of γ.

Table 4.3 shows summary statistics for the implied optimal relative tax rates (in logs). Reflecting their higher share of housework time in total working time, our model implies that, on average, women should be taxed at lower marginal rates, with a 90 log point gap to men. Such gap in tax rates would for example arise if, on average, men's

Table 4.3. Summary statistics on model-implied optimal relative intra-household marginal tax rates (for $\gamma = 0$), in logs.

	mean	std. dev.
all	0.00	0.718
female	-0.452	0.557
male	0.452	0.557

marginal tax rate is 42.5% and women's 17.5%, $\log(0.425/0.175) \approx 0.9$. This average gap between men and women can be addressed through gender-based taxation. There is, however, also substantial variation in optimal relative tax rates *within* gender, which by construction gender-based taxation cannot achieve. It is therefore a quantitative question how accurate gender-based taxation could achieve efficient intra-household taxation.

We now use regressions to quantify how closely different simple tax rules can explain optimal tax rates. We start with a comparison of three tax regimes and combinations of them. The first is joint taxation of married couples which is the status quo in the U.S. This system implies spouses are taxed at identical marginal rates, i.e., $\theta_{ijt} = \theta \; \forall \; ijt$. We conceptualize this regime by regressing optimal relative within-household tax rates on a constant only. The second regime is gender-based taxation, which we implement by regressing optimal rates on the individual's gender next to a constant. Third, we consider a regime of separate taxation where relative marginal tax rates in a couple depend on relative income. This can be achieved in a progressive income-tax system where married spouses file taxes individually rather than jointly. We implement this system by regressing optimal tax rates on log relative earnings next to a constant. The estimated coefficient on relative income can be understood as the degree of tax progressivity that maximizes intra-household tax efficiency. In addition, we consider an evaluation where we, rather than estimating the relative-income sensitivity, restrict this coefficient to the estimate of Heathcote, Storesletten, and Violante (2020) for the degree of progressivity of the current U.S. tax system. Their estimates imply that marginal rates increase in income with an elasticity of 0.18.

Table 4.4 compares these tax regimes, where optimal tax rate have been determined using our baseline estimates for gender-specific Frisch elasticities of total hours, see columns (3) and (4) in Table 4.1. By construction, taxing married couples jointly cannot

Table 4.4. Comparison of intra-household tax efficiency under joint taxation of married couples, gender-based taxation, progressive separate taxation, and combinations.

	(1) joint taxation	(2) gender-based	(3) progressive separate taxation: "optimal" base	(4) progressive separate taxation: "optimal" + gender	(5) progressive separate taxation: current base	(6) progressive separate taxation: current + gender
Constant	0.000	-0.452	0.000	-0.247	-0.000	-0.335
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Male		0.905		0.494		0.670
		(0.006)		(0.005)		(0.005)
Log rel. earn.			0.400	0.315	*0.180*	*0.180*
			(0.002)	(0.002)	—	—
Observations	35032	35032	35032	35032	35032	35032
R^2	0.000	0.397	0.592	0.685	0.413	0.632

Notes: Dependent variable is log relative optimal tax rate, θ^*_{ijt}. Relative earnings are measured in logs. Standard errors in parentheses. Coefficients without standard errors (in italics) are constrained coefficients.

capture any of the variation in optimal intra-household relative tax rates, see the first column. Against this benchmark, gender-based taxation improves intra-household tax efficiency as optimal relative tax rates correlate with gender. Setting men's tax rates between 90 and 135 log points above women's allows the government to capture about 40% of the variation in optimal relative tax rates, see the second column of Table 4.4.[96] To put these numbers into perspective, fix the average marginal tax rate of men and women at 30%. Then, a 90 log point difference implies men to be taxed at 42.5% and women at 17.5% marginal rates on average. For a 135 log points difference, these numbers would be 47.7% and 12.3%, respectively.

The third column shows the results for the alternative regime of separate taxation where relative tax rates vary with relative income (progressive taxation). A progressivity level of 0.40 would match optimal relative intra-household tax rates with an accuracy of about 60%. Interestingly, the estimated relative-income sensitivity is close to the degree of progressivity that Heathcote, Storesletten, and Violante (2017) estimate to balance optimally the trade-off between redistribution and insurance on the one hand and labor-supply incentives on the other hand, and only slightly larger than what Wu

[96] A value of $1-2\gamma = 1$ gives a coefficient of 90 log points, for other reasonable values of γ suggested by the literature, such as $1-2\gamma = 1.5$, the coefficient is scaled up by 50% to 135 log points.

and Krueger (2021) find to be optimal for married couples in an incomplete-markets model with endogenous labor supply.[97]

The fourth column in Table 4.4 studies progressive tax systems where tax rates are additonally conditioned on gender. This would result in a significant conditioning of tax rates on gender, but the respective cofficient is only roughly half of the estimate than in a tax system with only gender-based taxation, see column (2). If tax rates are conditioned on both, incomes and gender, there is an additional increase in accuracy compared to the purely income-based tax rule in the third column, but the increase is not very large (from about 60% to 69%).

Yet, both specifications (columns (3) and (4)) imply a substantially more progressive tax system than the status quo in the U.S., for which estimates for the elasticity of marginal tax rates to taxable income are about half as large. We therefore estimated specifications where we restrict the coefficient on relative incomes to 0.18, the estimate for the progressivity of the U.S. tax-transfer code by Heathcote, Storesletten, and Violante (2020). Columns (5) and (6) show the results. We find that the R^2 of the separate-taxation regression declines from about 60% to about 41%, which is still somewhat larger than in the regime of pure gender-based taxation. Interestingly, we find that the explanatory power of the restricted regression with both, gender-based taxation and progressivity, declines only mildly from about 69% to 63%. Importantly, both versions of progressive separate taxation match optimal intra-household tax rates better than gender-based taxation.

Ignoring relative housework time as a tax determinant. It is interesting to evaluate the mistake one would make if one were to ignore the endogenous dependence of labor-supply elasticities on the division of household chores and take all gender differences in labor-supply elasticities as being a direct consequence of gender. To assess this quantitatively, we repeat the previous analysis for counterfactual optimal marginal tax ratio that would arise when we erroneously interpreted the coefficients on the wage rates in *market labor supply regressions*, i.e., those in columns (1) and (2) of Table 4.1, as the labor-supply elasticities of *all* men and *all* women, respectively. These coefficients are in fact estimates of the *average* Frisch elasticities by gender, but the model implies

[97] The optimal degree of progressivity is usually reduced when endogenous skill investments are incorporated into the analysis.

Table 4.5. Comparison of intra-household tax efficiency under gender-based taxation, progressive separate taxation, and combinations, when endogenous dependence of labor-supply elasticities on division of household chores is ignored.

	(1)	(2)	(3)
	gender-	progressive separate	
	based	"optimal"	current
Constant	-0.632	0.000	0.000
	(0.000)	(0.003)	(0.003)
male	1.265		
	(0.000)		
Log rel. earn.		0.215	*0.180*
		(0.002)	—
Observations	35032	35032	35032
R^2	1.000	0.222	0.216

Notes: Dependent variable is log relative optimal tax rate, θ^*_{ijt}. Relative earnings are measured in logs. Standard errors in parentheses. Coefficients without standard errors (in italics) are constrained coefficients.

that there is heterogeneity of elasticities *within* gender as a consequence of differences in relative housework times of household members. Table 4.5 shows the results for the counterfactual optimal marginal tax ratios as dependent variables. By construction, one would conclude that gender-based taxation yields perfect intra-household tax efficiency (the R^2 in column (1) is one). In turn, efficiency gains from progressive and separate taxation were only about 20% of the possible gains (see columns (2) and (3)). Hence, ignoring the division of household chores as a determinant of labor-supply elasticities and optimal tax rates induces a serious overstatement of the efficiency gains from gender-based taxation and a substantial underestimation of the gains associated with separate taxation of married couples in a progressive system.

Sensitivity. To investigate how sensitive these results are with respect to the particular values used for gender-specific Frisch elasticities of total hours, we reconsider our analysis using the parameter estimates reported in columns (3) and (4) of Table 4.2. Table 4.6 summarizes the results. Overall, we find a similar set of results. In this specification, gender-based taxation explains even higher shares of optimal tax rates, but, in parallel, the explanatory power of the alternative tax regimes increases as well so that the main messages remain unaffected.

Table 4.6. Comparison of intra-household tax efficiency under joint taxation of married couples, alternative values for Frisch elasticities of total hours.

	(1)	(2)	(3)	(4)	(5)	(6)
	joint	gender-	progressive separate taxation			
	taxation	based	"optimal"		current	
			base	+ gender	base	+ gender
Constant	0.000	-0.514	0.000	-0.309	0.000	-0.397
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Male		1.028		0.617		0.793
		(0.006)		(0.005)		(0.005)
Log rel. earn.			0.420	0.315	*0.180*	*0.180*
			(0.002)	(0.002)	—	—
Observations	35032	35032	35032	35032	35032	35032
R^2	0.000	0.460	0.588	0.717	0.396	0.670

Notes: Dependent variable is log relative optimal tax rate, θ^*_{ijt}. Relative earnings are measured in logs. Standard errors in parentheses. Coefficients without standard errors (in italics) are constrained coefficients.

Although taxation based on relative incomes matches optimal relative tax rates better than pure gender-based taxation, income-based taxation has the disadvantage of being based on an endogenous tax-dependent variable thus giving rise to inefficient responses to tax rates while gender-based taxation can be viewed as a form of tagging (Cremer, Gahvari, and Lozachmeur 2010). We now investigate whether one can easily find tags which are better than gender in achieving intra-household tax efficiency.

Are there better tags than gender? Mankiw, Weinzierl, and Yagan (2009) discuss a number of potential tags for use in optimal tax systems, among them presence and number of children, gender, height, skin color, physical attractiveness, health, and parents' education. For instance, Mankiw and Weinzierl (2010) present a quantitative assessment of height-based taxation in a redistributive tax system. We now assess how well some of the tags proposed by Mankiw, Weinzierl, and Yagan (2009) are able to mimic predicted optimal intra-household tax rate ratios. Since number of children, skin color, and even parental education are highly correlated within couples, either by construction or due to assortative mating, we focus on body height and, as our measure of physical attractiveness, the body mass index (BMI).

Table 4.7 shows the comparison of different forms of tagging in income taxation, using the baseline numbers for optimal marginal tax ratios as dependent variable. For

Table 4.7. Comparison of intra-household tax efficiency under different forms of tagging in income taxation.

	(1) gender-based	(2) BMI	(3) height	(4) BMI & height
Constant	-0.454	0.000	-0.000	-0.000
	(0.004)	(0.004)	(0.003)	(0.003)
Male	0.908			
	(0.006)			
Log rel. BMI		0.882		0.353
		(0.016)		(0.015)
Log rel. height			3.846	3.539
			(0.033)	(0.035)
Observations	33358	33358	33358	33358
R^2	0.396	0.087	0.285	0.297

Notes: Dependent variable is log relative optimal tax rates, θ^*_{ijt}. All dependent variables except gender are measured in intra-household differences. Standard errors in parentheses. Body mass index (BMI) is $weight/height^2$.

completeness, we first reconsider gender-based taxation in the slightly different sample for which height and BMI are observed.[98] As before, gender-based taxation explains about 40% of the optimal intra-household relative marginal tax rates. Exclusively conditioning tax rates on the BMI (column (2)) yields a particularly low accuracy, also in comparison to gender-based taxation. Further, the positive coefficient on the BMI runs counter to the redistributive rationale implying to tax physical attractiveness (*low* BMI) which is associated with higher earnings. Using relative body height as a tag performs better (R^2 about 29%) than the BMI (and delivers a coefficient with a sign consistent with the redistributive motive), but worse than gender-based taxation. Also a combination of the BMI and body height without gender (column (4)) is inferior to purely gender-based taxation (column (1)).

Hence, if one is concerned about the efficiency losses arising from individuals' tax-dodging responses under progressive taxation, gender appears the dominant tag for taxes compared to the alternatives body height and physical attractiveness. Yet, it should be noted that the accuracy of progessive and separate taxation of married couples in matching intra-household tax efficiency exceeds that of gender-based taxation quite substantially. This means that even with some inefficient responses, progressive

[98]There are missing data on body height and BMI for some individuals.

separate taxation may still dominate gender-based taxation in terms of intra-household tax efficiency.

4.5 Conclusion

We have explored the roles of household specialization and gender differences in preferences in shaping labor-supply elasticities as well as their implications for optimal taxation. Our model of joint decision-making in dual-earner households has shown that optimal intra-household relative marginal tax rates depend on the relative housework times of household members and, if there are preference differences between women and men, gender. Our empirical results underscore the significance of household specialization, while also indicating the presence of gender-related factors beyond chore division. Our assessment of implementable tax rules has shown that there are potential efficiency gains from gender-based taxation. These gains are, however, dominated by gender-neutral progressive tax systems with separate taxation of married couples.

Appendix 4.A Theoretical model

Subsection 4.A.1 Household optimization

The Lagrangian of the household problem is

$$\max_{\{c_{jt},d_{jt},\{n_{ijt},h_{ijt}\}_i\}_t} \mathcal{L}_j = E_0 \sum_{t=0}^{\infty} \beta^t \Bigg\{ \sum_i \mu_{ijt} u_{ijt} + \lambda_{jt} \left(\sum_i w_{ijt}^{net} n_{ijt} + (1+r_t)\, a_{jt} - c_{jt} - a_{jt+1} \right) + \lambda_{jt}^d \left(f\left(\{h_{ijt}\}_i\right) - d_{jt}\right) + \xi_{jt}\left(a_{jt+1} - a_t^{\min}\right) \Bigg\}$$

The first-order conditions for c_{jt}, d_{jt}, n_{ijt}, and h_{ijt} are (4.5) - (4.8) and the one for a_{jt+1} is

$$\lambda_{jt} - \xi_{jt} = \beta E_t \left[\lambda_{jt+1}\left(1 + r_{t+1}\right) + \sum_i \frac{\partial \mu_{ijt+1}}{\partial a_{jt+1}} u_{ijt} \right].$$

Combining (4.5) with (4.7) and using $\partial v_{jt}/\partial x = \beta^t \partial U_j/\partial x$ for any choice variable x gives (4.9). Combining (4.6) with (4.8) and using $\partial v_{jt}/\partial x = \beta^t \partial U_j/\partial x$ as well as $\partial U_j/\partial n_{ijt} = \partial U_j/\partial h_{ijt}$ gives (4.10).

Subsection 4.A.2 Government optimization and optimal taxation

The maximization problem of the government is

$$\max_{\tau_{ijt},\tau_{-ijt}} U_j\left(c_{jt}, d_{jt}, h_{ijt}, h_{-ijt}, n_{ijt}, n_{-ijt}\right),$$

subject to (4.17). The first-order condition is (4.18).

Substituting the household optimality conditions (4.9) and (4.10) into the first-order condition for the government gives

$$\begin{aligned}
&\frac{\partial U_j}{\partial c_{jt}} \frac{\partial c_{jt}}{\partial \tau_{ijt}} + \frac{\partial U_j}{\partial c_{jt}} \frac{(1-\tau_{ijt}) w_{ijt}}{\partial f/\partial h_{ijt}} \frac{\partial d_{jt}}{\partial \tau_{ijt}} \\
&- \frac{\partial U_j}{\partial c_{jt}} (1-\tau_{ijt}) w_{ijt} \frac{\partial h_{ijt}}{\partial \tau_{ijt}} - \frac{\partial U_j}{\partial c_{jt}} (1-\tau_{-ijt}) w_{-ijt} \frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \\
&- \frac{\partial U_j}{\partial c_{jt}} (1-\tau_{ijt}) w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} - \frac{\partial U_j}{\partial c_{jt}} (1-\tau_{-ijt}) w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}}
\end{aligned}$$

$$+ \lambda_{jt}^G \cdot \left(w_{ijt} n_{ijt} + \tau_{ijt} w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \tau_{-ijt} w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \right) = 0 \; \forall \; i.$$

Rearranging yields

$$\begin{aligned} \frac{\partial U_j}{\partial c_{jt}} \Bigg[\frac{\partial c_{jt}}{\partial \tau_{ijt}} &+ \frac{(1-\tau_{ijt}) w_{ijt}}{\partial f / \partial h_{ijt}} \frac{\partial d_{jt}}{\partial \tau_{ijt}} \\ &- (1-\tau_{ijt}) w_{ijt} \frac{\partial h_{ijt}}{\partial \tau_{ijt}} - (1-\tau_{-ijt}) w_{-ijt} \frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \\ &- (1-\tau_{ijt}) w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} - (1-\tau_{-ijt}) w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \Bigg] \\ &+ \lambda_{jt}^G \cdot \left(w_{ijt} n_{ijt} + \tau_{ijt} w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \tau_{-ijt} w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \right) = 0. \end{aligned}$$

The responses of c_{jt} and d_{jt} to the tax rates can be determined through the household constraints (4.2) and (4.3). Applying $a_{jt+1} = (1 + r_t) a_{jt}$ in the household budget constraint (4.2) gives

$$c_{jt} = \sum_i (1 - \tau_{ijt}) w_{ijt} n_{ijt},$$

which yields

$$\frac{\partial c_{jt}}{\partial \tau_{ijt}} = -w_{ijt} n_{ijt} + (1-\tau_{ijt}) w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} + (1-\tau_{-ijt}) w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}}.$$

Further, for the housework production function (4.3), it holds that

$$\frac{\partial d_{jt}}{\partial \tau_{ijt}} = \frac{\partial f}{\partial h_{ijt}} \frac{\partial h_{ijt}}{\partial \tau_{ijt}} + \frac{\partial f}{\partial h_{-ijt}} \frac{\partial h_{-ijt}}{\partial \tau_{ijt}}.$$

Using these results in the optimal-tax condition gives

$$\begin{aligned} \frac{\partial U_j}{\partial c_{jt}} \Bigg[-w_{ijt} n_{ijt} &+ (1-\tau_{ijt}) w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} + (1-\tau_{-ijt}) w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \\ &+ \frac{(1-\tau_{ijt}) w_{ijt}}{\partial f / \partial h_{ijt}} \left(\frac{\partial f}{\partial h_{ijt}} \frac{\partial h_{ijt}}{\partial \tau_{ijt}} + \frac{\partial f}{\partial h_{-ijt}} \frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \right) \\ &- (1-\tau_{ijt}) w_{ijt} \frac{\partial h_{ijt}}{\partial \tau_{ijt}} - (1-\tau_{-ijt}) w_{-ijt} \frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \\ &- (1-\tau_{ijt}) w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} - (1-\tau_{-ijt}) w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \Bigg] \\ &+ \lambda_{jt}^G \cdot \left(w_{ijt} n_{ijt} + \tau_{ijt} w_{ijt} \frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \tau_{-ijt} w_{-ijt} \frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \right) = 0 \end{aligned}$$

which can be simplified to

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \tau_{ijt}} =& \frac{\partial U_j}{\partial c_{jt}} \Bigg[-w_{ijt}n_{ijt} + \frac{(1-\tau_{ijt})w_{ijt}}{\partial f/\partial h_{ijt}} \left(\frac{\partial f}{\partial h_{ijt}} \frac{\partial h_{ijt}}{\partial \tau_{ijt}} + \frac{\partial f}{\partial h_{-ijt}} \frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \right) \\ & -(1-\tau_{ijt})w_{ijt}\frac{\partial h_{ijt}}{\partial \tau_{ijt}} - (1-\tau_{-ijt})w_{-ijt}\frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \Bigg] \\ & + \lambda^G_{jt} \cdot \left(w_{ijt}n_{ijt} + \tau_{ijt}w_{ijt}\frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \tau_{-ijt}w_{-ijt}\frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \right) = 0.\end{aligned}$$

From (4.10) it follows that $(1-\tau_{ijt})w_{ijt}/(\partial f/\partial h_{ijt})$ is the same for both household members i and $-i$. Using this in the optimal-tax condition and multiplying out gives

$$\begin{aligned}& \frac{\partial U_j}{\partial c_{jt}} \Bigg[-w_{ijt}n_{ijt} + \frac{(1-\tau_{ijt})w_{ijt}}{\partial f/\partial h_{ijt}} \frac{\partial f}{\partial h_{ijt}} \frac{\partial h_{ijt}}{\partial \tau_{ijt}} + \frac{(1-\tau_{-ijt})w_{-ijt}}{\partial f/\partial h_{-ijt}} \frac{\partial f}{\partial h_{-ijt}} \frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \\ & -(1-\tau_{ijt})w_{ijt}\frac{\partial h_{ijt}}{\partial \tau_{ijt}} - (1-\tau_{-ijt})w_{-ijt}\frac{\partial h_{-ijt}}{\partial \tau_{ijt}} \Bigg] \\ & + \lambda^G_{jt} \cdot \left(w_{ijt}n_{ijt} + \tau_{ijt}w_{ijt}\frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \tau_{-ijt}w_{-ijt}\frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \right) = 0.\end{aligned}$$

In the square brackets, all but the first term cancel, which gives

$$-\frac{\partial U_j}{\partial c_{jt}} w_{ijt}n_{ijt} + \lambda^G_{jt} \cdot \left(w_{ijt}n_{ijt} + \tau_{ijt}w_{ijt}\frac{\partial n_{ijt}}{\partial \tau_{ijt}} + \tau_{-ijt}w_{-ijt}\frac{\partial n_{-ijt}}{\partial \tau_{ijt}} \right).$$

Dividing by $w_{ijt}n_{ijt}$ yields (4.19).

Subsection 4.A.3 Approximation of the Frisch elasticity of labor supply

Applying the functional form of the utility function gives

$$\begin{aligned} u_{ijt} &= v_{g(i),c}(c_{jt}) + v_{g(i),d}\left(d_{jt}\right) - \psi_{g(i)} \cdot \frac{l_{ijt}^{1+1/\eta_{g(i)}}}{1+1/\eta_{g(i)}}\ , \text{ with} \\ \frac{\partial u_{ijt}}{\partial n_{ijt}} &= -\psi_{g(i)} l_{ijt}^{1/\eta_{g(i)}}. \end{aligned}$$

Using this in the first-order condition for market labor supply n_{ijt} (4.7) yields

$$\mu_{ijt}\psi_i \cdot l_{ijt}^{1/\eta_{g(i)}} = \lambda_{jt} w_{ijt}^{net},$$

and solved for l_{ijt}

$$l_{ijt} = \frac{\lambda_{jt}^{\eta_{g(i)}}(w_{ijt}^{net})^{\eta_{g(i)}}}{\mu_{ijt}^{\eta_{g(i)}}\psi_i^{\eta_{g(i)}}}.$$

A first-order Taylor approximation gives

$$\begin{aligned}
\log l_{ijt} &= \eta_{g(i)}\log\lambda_{jt} + \eta_{g(i)}\log(w_{ijt}^{net}) - \eta_{g(i)}\log\mu_{ijt} - \eta_{g(i)}\log\psi_i \\
\log l_{ijt} + \frac{1}{\bar{l}_{ij}}\left(l_{ijt} - \bar{l}_{ij}\right) &= \eta_{g(i)}\log\lambda_{jt} + \frac{\eta_{g(i)}}{\overline{\lambda}_{ij}}\left(\lambda_{ijt} - \overline{\lambda}_{ij}\right) + \eta_{g(i)}\log(w_{ijt}^{net}) \\
&\quad + \frac{\eta_{g(i)}}{\overline{w}_{ij}^{net}}\left(w_{ijt}^{net} - \overline{w}_{ij}^{net}\right) - \eta_{g(i)}\log\mu_{ijt} \\
&\quad - \frac{\eta_{g(i)}}{\overline{\mu}_{ij}}\left(\mu_{ijt} - \overline{\mu}_{ij}\right) - \eta_{g(i)}\log\psi_i - \frac{\eta_{g(i)}}{\overline{\psi}_i}\left(\psi_i - \overline{\psi}_i\right) \\
\frac{1}{\bar{l}_{ij}}\left(l_{ijt} - \bar{l}_{ij}\right) &= \frac{\eta_{g(i)}}{\overline{\lambda}_{ij}}\left(\lambda_{ijt} - \overline{\lambda}_{ij}\right) + \frac{\eta_{g(i)}}{\overline{w}_{ij}^{net}}\left(w_{ijt}^{net} - \overline{w}_{ij}^{net}\right) - \frac{\eta_{g(i)}}{\overline{\mu}_{ij}}\left(\mu_{ijt} - \overline{\mu}_{ij}\right) \\
\widehat{l}_{ijt} &= \eta_{g(i)}\widehat{w}_{ijt}^{net} + \eta_{g(i)}\widehat{\lambda}_{jt} - \eta_{g(i)}\widehat{\mu}_{ijt},
\end{aligned}$$

where the last equation is equivalent to (4.11) in the main text, and for a generic variable $x = l,\ n,\ h,\ \lambda,\ w$, $\widehat{x} = \log\left(x/\overline{x}\right) \approx \frac{x-\bar{x}}{\bar{x}}$ and $\overline{x}$ is the point of approximation.

To derive the elasticity of *market labor supply*, first use the definition $l_{ijt} = n_{ijt} + h_{ijt}$ to log-linearize, with $\widehat{x} = \log\left(x/\overline{x}\right) \approx \frac{x-\bar{x}}{\bar{x}}$

$$\begin{aligned}
\log l_{ijt} &= \log(n_{ijt} + h_{ijt}) \\
\log l_{ijt} + \frac{1}{\bar{l}_{ij}}(l_{ijt} - \bar{l}_{ij}) &= \log(n_{ijt} + h_{ijt}) + \frac{1}{\overline{n}_{ij} + \overline{h}_{ij}}(n_{ijt} - \overline{n}_{ij}) + \frac{1}{\overline{n}_{ij} + \overline{h}_{ij}}(h_{ijt} - \overline{h}_{ij}) \\
\frac{1}{\bar{l}_{ij}}(l_{ijt} - \bar{l}_{ij}) &= \frac{1}{\overline{n}_{ij} + \overline{h}_{ij}}(n_{ijt} - \overline{n}_{ij}) + \frac{1}{\overline{n}_{ij} + \overline{h}_{ij}}(h_{ijt} - \overline{h}_{ij}) \\
\frac{1}{\bar{l}_{ij}}(l_{ijt} - \bar{l}_{ij}) &= \frac{\overline{n}_{ij}}{\overline{n}_{ij} + \overline{h}_{ij}}\frac{(n_{ijt} - \overline{n}_{ij})}{\overline{n}_{ij}} + \frac{\overline{h}_{ij}}{\overline{n}_{ij} + \overline{h}_{ij}}\frac{(h_{ijt} - \overline{h}_{ij})}{\overline{h}_{ij}} \\
\widehat{l}_{ijt} &= \frac{\overline{n}_{ij}}{\bar{l}_{ij}}\widehat{n}_{ijt} + \frac{\overline{h}_{ij}}{\bar{l}_{ij}}\widehat{h}_{ijt},
\end{aligned}$$

which is equivalent to (4.12) in the main text. Combine (4.11) and (4.12) and solve for market hours $\widehat{n}_{ijt}$

$$\begin{aligned}
\frac{\overline{n}_{ij}}{\bar{l}_{ij}}\widehat{n}_{ijt} + \frac{\overline{h}_{ij}}{\bar{l}_{ij}}\widehat{h}_{ijt} &= \eta_{g(i)}\widehat{w}_{ijt}^{net} + \eta_{g(i)}\widehat{\lambda}_{jt} - \eta_{g(i)}\widehat{\mu}_{ijt} \\
\widehat{n}_{ijt} &= \frac{\bar{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{w}_{ijt}^{net} - \frac{\bar{l}_{ij}}{\overline{n}_{ij}}\frac{\overline{h}_{ij}}{\bar{l}_{ij}}\widehat{h}_{ijt} + \frac{\bar{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{\lambda}_{jt} - \frac{\bar{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{\mu}_{ijt},
\end{aligned}$$

to obtain

$$\widehat{n}_{ijt} = \frac{\bar{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{w}^{net}_{ijt} - \frac{\overline{h}_{ij}}{\overline{n}_{ij}}\widehat{h}_{ijt} + \frac{\bar{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{\lambda}_t - \frac{\bar{l}_{ij}}{\overline{n}_{ij}}\eta_{g(i)}\widehat{\mu}_{ijt}.$$

which is equivalent to (4.13) in the main text. Hence, the *Frisch elasticity of market work* is given by

$$e^{Frisch}_{ijt} = \frac{\partial \widehat{n}_{ijt}}{\partial \widehat{w}^{net}_{ijt}}|_{\lambda,\mu} = \frac{\bar{l}_{ij}}{\overline{n}_{ij}} \cdot \eta_{g(i)} - \frac{\overline{h}_{ij}}{\overline{n}_{ij}} \cdot \frac{\partial \widehat{h}_{ijt}}{\partial \widehat{w}^{net}_{ijt}}|_{\lambda,\mu} \approx \frac{\bar{l}_{ij}}{\overline{n}_{ij}} \cdot \eta_{g(i)},$$

which is equivalent to (4.14) in the main text. Using the result for the Frisch elasticity in the ratio of optimal marginal tax rates (4.22) gives

$$\frac{\tau^*_{ijt}}{\tau^*_{-ijt}} = \frac{e^{Frisch}_{-ijt}}{e^{Frisch}_{ijt}} = \frac{\eta_{g(-i)} \cdot \bar{l}_{-ij}/\overline{n}_{-ij}}{\eta_{g(i)} \cdot \bar{l}_{ij}/\overline{n}_{ij}} = \frac{\eta_{g(-i)}}{\eta_{g(i)}} \cdot \frac{\left(\overline{n}_{-ij}/\bar{l}_{-ij}\right)^{-1}}{\left(\overline{n}_{ij}/\bar{l}_{ij}\right)^{-1}} = \frac{\eta_{g(-i)}}{\eta_{g(i)}} \cdot \frac{\overline{n}_{ij}/\bar{l}_{ij}}{\overline{n}_{-ij}/\bar{l}_{-ij}}.$$

Appendix 4.B Marginal propensity to earn out of unearned income

We briefly review the empirical literature on the marginal propensity to earn out of unearned income, or the wealth effect on labor supply. Many empirical studies point to zero or small labor-supply responses to changes in unearned income. For example, Schmitt-Grohé and Uribe (2012) estimate an RBC model and find the wealth effect on labor supply to be essentially zero. This is in line with several microeconometric studies on the effects of cash transfers. Marinescu (2018) summarizes studies with quasi-experimental research designs while the results of several field experiments conducted in developing countries are reviewed by Banerjee et al. (2017) and Bastagli et al. (2016), all three concluding that cash transfer have little to no negative effect on labor supply.[99] Exploiting lottery wins whose small likelihood makes them almost exogenous, Imbens,

[99] Synthesizing empirical findings regarding the effects of the negative income tax experiments of the 1970s in a structural model, Robins (1985) finds that the marginal propensity to consume out of unearned income varies between -0.06 and -0.10. Akee et al. (2010) use a difference-in-differences approach exploiting casino transfers to native American families, finding the additional (unearned) income did not induce any change in labor supply. Jones and Marinescu (2022) apply a synthetic-control approach to the Alaska Permanent Fund Dividend paid unconditionally to Alaskan citizens. The results show that the payment has has no impact on the employment-to-population ratio in Alaska, although it cannot be ruled out that some wealth effect exists but is offset by positive macro effects, i.e., rising wage rates.

Rubin, and Sacerdote (2001), Cesarini et al. (2017), and Picchio, Suetens, and van Ours (2018) estimate labor supply responses that also imply very moderate marginal propensities to earn out of unearned income.[100] The trove of evidence pointing to very small wealth effects induced the construction of utility functions in line with this property (Greenwood, Hercowitz, and Huffman 1988; Jaimovich and Rebelo 2009) and many macroeconomic studies use models with the assumption that income effects are essentially negligible (Auclert, Bardóczy, and Rognlie 2023; Bredemeier, Juessen, and Winkler 2023; Dyrda and Pedroni 2023; Wolf 2023).

Yet, there are also papers that estimate somewhat larger wealth effects on labor supply. Gromadzki (2023) exploits the design of a child benefit program in Poland and estimates a marginal propensity to earn out of unearned income of -0.14. Gelber, Moore, and Strand (2017) exploit a regression discontinuity in eligibility to disability insurance payments in the U.S. and estimate the marginal propensity to earn out of unearned income to be -0.2. Kimball and Shapiro (2008) have used hypothetical lottery wins (i.e., they asked survey respondents how they would react to winning a lottery) and they have arrived at estimates for the marginal propensity close to -0.3. The same number is reported by Bengtsson (2012) who considers a reform to unconditional cash transfer in South Africa. The largest microeconometric estimate we are aware of is -0.51 and reported by Golosov et al. (2024) who apply an event-study design exploiting variation in the timing of lottery wins. Khan and Tsoukalas (2012) report a wealth effect of -0.6 in an estimated New Keynesian model with news shocks.

To summarize, the marginal propensity to earn out of unearned income is mostly estimated to be negligible or moderate at best. Estimates lie between 0 and -0.6.

[100] Cesarini et al. (2017) and Picchio, Suetens, and van Ours (2018) estimate how couple households adjust labor earnings to changes in unearned income in the form of one-time windfalls. Both studies observe reductions in earnings for a few years. In the year of the windfall, household earnings fall by 1.4% (Cesarini et al. 2017) or 1.8% (Picchio, Suetens, and van Ours 2018) of the rise in unearned income, respectively. An upper bound for the strength of the effect can be obtained by multiplying the immediate response with the average remaining years in the labor market as calculated by Cesarini et al. (2017). Doing so gives a maximum marginal propensity to earn out of unearned income of -0.225 in the case of Cesarini et al. (2017) and -0.358 in the case of Picchio, Suetens, and van Ours (2018). Imbens, Rubin, and Sacerdote (2001) consider changes in unearned income in the form of yearly installments and therefore do not need to differentiate between immediate and later responses, yet their analysis is only with regard to individual earnings. They find the individual propensity to earn out of individual unearned income to be about 11%. Similarly, Jacob and Ludwig (2012) finds a small labor supply responses to being successful in a housing voucher lottery in Chicago, implying a marginal propensity of -0.09.

Table 4.C.1. Market hours and total hours regressions, sample of couples without young children.

	(1)	(2)	(3)	(4)
	log market hours, $\log n_{ijt}$		log total hours, $\log l_{ijt}$	
	men	women	men	women
log wage rate, $\log w_{ijt}$	0.633^{***}	0.930^{***}	0.412^{***}	0.395^{***}
	(0.0523)	(0.0890)	(0.0388)	(0.0471)
log housework, $\log h_{ijt}$	-0.0394^{***}	-0.113^{***}		
	(0.00587)	(0.0115)		
Observations	12522	12522	12522	12522

Notes: Restricted sample without children below age 7. Dependent variables are log hours worked in the market, $\log n_{ijt}$ (columns (1) and (2)), and log total hours worked, $\log l_{ijt}$ (columns (3) and (4)). All regressions include individual and time fixed effects, taste shifters (number of young kids, number of old kids, cubic in age), log household consumption, log share of food expenditures, and a constant. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix 4.C Additional regression results

Table 4.C.1 show the results of gender-specific labor-supply regressions for a restricted sample of couples without young children. Table 4.C.2 shows results of labor-supply regressions in the full sample when we correct for selection into the labor force among women. In Table 4.C.2, regressions for men are unchanged compared to the baseline regressions (Table 4.1) and results are repeated for convenience.

Table 4.C.2. Market hours and total hours regressions, controlling for selection effects.

	(1)	(2)	(3)	(4)
	log market hours, $\log n_{ijt}$		log total hours, $\log l_{ijt}$	
	men	women	men	women
log wage rate, $\log w_{ijt}$	0.602^{***}	1.137^{***}	0.380^{***}	0.449^{***}
	(0.0455)	(0.0818)	(0.0337)	(0.0420)
log housework, $\log h_{ijt}$	-0.0415^{***}	-0.141^{***}		
	(0.0049)	(0.0100)		
Observations	17516	17516	17516	17516

Notes: Dependent variables are log hours worked in the market, $\log n_{ijt}$ (columns (1) and (2)), and log total hours worked, $\log l_{ijt}$ (columns (3) and (4)). All regressions include individual and time fixed effects, taste shifters (number of young kids, number of old kids, cubic in age), log household consumption, log share of food expenditures, an inverse Mills term estimated using a probit model for female labor-force participation as described in the main text, and a constant. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5 Concluding Remarks

This thesis has explored the labor-market outcomes of men and women from a family-economics perspective. A particular focus has been the role of the family for gender differences in labor market choices. By doing so, this work offers additional groundwork for more equitable and informed labor market policies.

First, in Chapter 2 (joint work with Christian Bredemeier and Falko Jüßen), we have proposed a simple way to embed family-economics arguments for pay differences between genders into standard decomposition techniques. To account appropriately for the role of the family in the determination of wages, one has to compare men and women with similar own characteristics *and similar partners*. We have set up a theoretical model that allows for a spill-over channel, through which wages depend positively on partner characteristics, and for a career-prioritization channel, through which wages depend negatively on partner characteristics. Standard decompositions ignore both channels and, thus, misestimate the share of the wage gap that is due to observable differences between men and women. When the career-prioritization is the dominant channel from partner characteristics to wages, too small a share is assigned to observable differences. We have proposed an extended decomposition approach that accounts for the role of the family through including partner characteristics. This approach corrects the bias successfully. In U.S. survey data, we have found that our extended decomposition explains considerably more of the wage gap than a standard approach – in line with our theory that highlights the role of career prioritization in dual-earner couples.

Next, in Chapter 3, I have used the striking regional differences between both women's accumulation of labor-market experience and the gender wage gap within Germany to investigate different family choices in East and West Germany. I have shown that differences in accumulated labor-market experience play a dominant role for understanding this "gap in the gap", that these differences are not due to particularities of East German employers or workers, and that they cannot be attributed to a stronger readiness for career interruptions by East German fathers. The East German case does not lend support to policies for family-friendly workplaces or fathers' child-care leaves; instead, if seeking to emulate its rather gender-egalitarian environment, policy should focus on expanding public daycare provision, where East Germany does still stand out.

Finally, in Chapter 4 (joint work with Christian Bredemeier and Falko Jüßen), we have investigated the quantitative role of household chores and preferences as determinants of gender differences in labor-supply elasticities as well as their implications for optimal taxation. In our model of joint decision-making in dual-earner households, we have derived how optimal tax rates depend on gender and chore division. Using PSID data, we have found empirical support for the importance of chore division, with gender playing some additional role. Our assessment of implementable tax rules has shown that there are potential efficiency gains from gender-based taxation. These gains are, however, dominated by gender-neutral progressive tax systems with separate taxation of married couples.

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