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Decomposing gender wage gaps: a family economics perspective

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Abstract

We propose 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 with similar partners. In US survey data, we find 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.

Keywords: Gender wage gap; wage-gap decomposition; dual-earner households; discrimination

JEL classification: J31; J16; J12; J71; J24

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). On average, women in the United States continue to earn close to 20 percent less per hour than men. As shown by, for example, 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 by women catching up in terms of human capital (i.e., education and experience). However, an open question remains as to why the

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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 7–9 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-paid jobs and less steep career paths.¹ Several studies have documented that a part of the wage gap can be attributed to such factors, but their quantitative role seems to be limited (Mueller and Plug, 2006; Le et al., 2011; Nyhus and Pons, 2012; Heinz et al., 2016; Chen et al., 2017; Flinn et al., 2018; Jung et al., 2018; Reuben et al., 2015; Roussille, 2022).

The second approach emphasizes the role of the family for the gender wage gap. An important dimension is women's relative temporal inflexibility due to their dominant role in childcare and non-market work in many families (e.g., Goldin, 2014; Almås et al., 2023; Cortés and Pan, 2023). At the same time, many husbands are their families' primary breadwinners and see their careers prioritized in many decisions of the family such as migration decisions (see, e.g., Mincer, 1978; Compton and Pollak, 2007; Foged, 2016; Braun et al., 2021), the choice of employers (see, e.g., Bredemeier, 2019; 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 explanations for the wage gap into standard decomposition techniques. The key common aspect of the family-based explanations 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 depend not only 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, in order to account appropriately for the role of the family for wages.

¹There is a significant empirical literature, mostly experimental, on gender differences in non-cognitive abilities, personality traits, and preferences, including the willingness to compete (Gneezy et al., 2009; Flory et al., 2015; Buser and Yuan, 2019), negotiation styles (Babcock and Laschever, 2003; Exley et al., 2020), promotion-seeking (Bosquet et al., 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).

For the Oaxaca–Blinder decomposition approach, which remains the most frequently applied decomposition approach of the gender wage gap, this means that the wage equation should include the characteristics of the individual's partner. For instance, a worker's own education should be included in the equation for the worker's wage – 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., Meara et al., 2020; Strittmatter and Wunsch, 2021) 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 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 for 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 to choose to live closer to the place that optimally promotes 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, which we call the spill-over channel, induces a positive relation between one's own wage and a 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 decomposition that ignores partner characteristics misestimates the fraction of the wage gap that is due to observable characteristics (i.e., the explained part of the gap). Whether the explained gap is overestimated or underestimated 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 delivers unbiased results.²

We apply our improved decomposition to US data from the Panel Study of Income Dynamics (PSID). In line with the literature, we document that standard 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 assign larger shares of the wage gap to 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 percent 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.

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 might also depend on their partners' 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 by only estimating a wage equation for men, for which selection is less an issue, and to use it to determine a counterfactual wage prediction for women. When we do so for a broad (and hence less

²Importantly, 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 in which 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.

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 with a standard approach. Finally, we find that, for singles and for married workers without a working partner, 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. This further supports the view that the family plays an important role for the gender wage gap.

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. 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.³ Moreover, career prioritization amplifies both non-discriminatory and discriminatory differences in earnings potentials: a family observing discrimination against women faces incentives to prioritize the husband's career over the wife's even if the two are identical in terms of objective characteristics. Policy can 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.

The remainder of this paper is organized as follows. In Section 2, we review additional related literature. We present the model in Section 3 and, in Section 4, we compare alternative decomposition approaches. In Section 5, we present our empirical analysis. We conclude in Section 6.

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 US 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

³For example, empirical evidence shows that female labor supply and hence the accumulation of work experience is affected by gender identity norms (Bertrand et al., 2015) and cultural factors (Blau et al., 2020).

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 with higher earnings potentials than themselves and that top-potential women remain without a 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 gender gaps even without systematic gender differences in the overall population. Their argument is similar to ours as it points to a channel that leads to women not realizing their earnings potentials because of family decisions responding 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.

While we remain 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:

Cortés and Tessada (2011) and Cortés and Pan (2019) emphasize temporal inflexibility of secondary earners. 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 childcare 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.

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 childcare provider in most households. Bredemeier (2019) shows that married individuals' labor supply to individual firms becomes less wage sensitive when they are married to spouses with high earnings, which monopsonistic firms can exploit to compress wages of secondary earners.

Hotz et al. (2018) show that women switch to more “family-friendly” jobs upon motherhood. Pertold-Gebicka et al. (2016) show that women around motherhood switch from private sector jobs with time pressure and returns to long hours to public sector jobs after the birth of a child. 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 et al. (2017) show that women have already taken such decisions in response to intended fertility and not only when children have been born. Wasserman (2023) shows that women have already entered more family-friendly jobs early in their career, presumably in anticipation of future family obligations. Wiswall and Zafar (2018) show that, among college students – almost all of which do not yet have children – women already have a higher willingness to pay for family-friendly job attitudes.

Foged (2016) provides a model of the joint location choice of dual-earner households but focuses on the extensive-margin choice of whether to move to another location rather than the intensive-margin choice of where to locate, which is the focus of our model. 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. 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, the husband’s education explains the propensity of couples to migrate to large metropolitan areas. Braun et al. (2021) shows that families migrate more often when they have a clear primary earner.

Another dimension where family decisions affect both the 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 afford the search for high-wage jobs for men. A counteracting effect of joint search behavior 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.

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 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 3.2.

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 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 childcare obligations. On the one hand, y should be understood as choices that are mutually beneficial to both members' careers, such as the formation of a network that both members can benefit from. On the other hand, 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 the "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 consists of three elements,

$$W_i = \psi_i z_{i,r} y I, \quad (1)$$

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

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

If the individual is in a location that differs from their 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

$$c_{I,r} = W_i + W_{-i} - \frac{1}{\eta}y^2. \quad (3)$$

The parameter η measures the productivity, or inverse cost, of the career investment y . It will determine the amount of 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 equations (1), (2), and (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

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

The optimal choices for location r and investment y are given by

$$r_I^* = \frac{\psi_i}{\psi_i + \psi_{-i}}a_i + \frac{\psi_{-i}}{\psi_i + \psi_{-i}}a_{-i} \quad (4)$$

and

$$y_I^* = \frac{\eta}{2} \left(\psi_i + \psi_{-i} - \frac{\psi_i\psi_{-i}}{(\psi_{-i} + \psi_i)^2}(a_i - a_{-i})^2 \right). \quad (5)$$

Equation (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 (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 , however, an individual's 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 (4) and (5) to obtain equilibrium log wages w_i :

$$w_i = \log \psi_i + \log \left(1 - \left(\frac{\psi_{-i}}{\psi_i + \psi_{-i}} (a_{-i} - a_i) \right)^2 \right) + \log \frac{\eta}{2} \left(\psi_i + \psi_{-i} - \frac{\psi_i \psi_{-i}}{(\psi_i + \psi_{-i})^2} (a_i - a_{-i})^2 \right). \quad (6)$$

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.

3.2. Marriage-market stage

To characterize the distribution of individual characteristics in marriages, 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 – that is, 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 the set of women by F and the set of men by M . In a marriage formed by woman i and man $-i$, we denote the wife's utility as $u_f(i, -i)$ and the husband's utility as $u_m(i, -i)$. In our model, $v_f(i, -i) = v_m(i, -i)$.

For the marriage market to be in equilibrium, no two individuals can 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

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

while, at the same time,

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

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

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

and

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

Using the results from Section 3.1, we obtain

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

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.

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.

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 $\gamma_m \neq \gamma_f$).

To obtain a log-linear relation between wages and characteristics, we apply a first-order Taylor approximation of the equilibrium wage equation (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 (6) taking its expected value $2(1 - \kappa)\sigma^2$.⁴ 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 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.⁵

Applying the approximation gives

$$w_i \approx \beta_0 + \beta_{1,g(i)}Z_i + \beta_{2,g(i)}Z_{-i} + \varepsilon_i, \tag{7}$$

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

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

See Online Appendix A for a derivation. Condition (7) can be read as a regression equation: β_0 is a constant, $\beta_{1,g(i)}$ and $\beta_{2,g(i)}$ are vectors of

⁴The expected value of $(a_{-i} - a_i)^2$ is $E(a_i - a_{-i})^2 = E(a_i^2 - 2a_i a_{-i} + a_{-i}^2) = 2E(a_i^2) - 2E(a_i a_{-i}) = 2(E(a^2) - E(a)^2 - \text{cov}(a_i, a_{-i})) = 2(\text{var}(a) - \text{cov}(a_i, a_{-i})) = 2(\sigma^2 - \kappa\sigma^2) = 2(1 - \kappa)\sigma^2$.

⁵Note 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.

coefficients, and ε_i is a (mean-zero) residual because 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).

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

$$\Delta = \underbrace{(\beta_{1,m} - \beta_{2,m}) \cdot (\bar{Z}_m - \bar{Z}_f)}_{\Delta|_Z} + \underbrace{(\beta_{1,m} - \beta_{1,f}) \cdot \bar{Z}_f + (\beta_{2,m} - \beta_{2,f}) \cdot \bar{Z}_m}_{\Delta|_\beta}, \quad (8)$$

where \bar{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 effect 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.

4.1. 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.⁶

$$w_i = b_{0,g(i)} + b_{1,g(i)} \cdot X_i + e_i, \quad (9)$$

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.

⁶While estimating the wage equation for women is in principle possible, the literature usually uses the estimated wage equation for men as it is more likely to capture discrimination-free returns to characteristics.

The empirical decomposition yields an “explained” part of the gap,

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

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

$$(\widehat{\Delta}|_b)^{std} = \widehat{b}_{0,m}^{std} - \widehat{b}_{0,f}^{std} + (\widehat{b}_{1,m}^{std} - \widehat{b}_{1,f}^{std})\bar{X}_f, \quad (10)$$

that this approach identifies as unrelated to observable characteristics.

4.2. 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

$$w_i = b_{0,g(i)} + b_{1,g(i)} \cdot X_i + b_{2,g(i)} \cdot X_{-i} + e_i, \quad (11)$$

which yields an explained gap of

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

and an unexplained gap of

$$(\widehat{\Delta}|_b)^{ext} = \widehat{b}_{0,m}^{ext} - \widehat{b}_{0,f}^{ext} + (\widehat{b}_{1,m}^{ext} - \widehat{b}_{1,f}^{ext})\bar{X}_f + (\widehat{b}_{2,m}^{ext} - \widehat{b}_{2,f}^{ext})\bar{X}_m. \quad (12)$$

If the set of 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 that are due to differences in these characteristics and due to differences in coefficients ($\Delta|_Z$ and $\Delta|_\beta$), respectively. This is not surprising as the wage equation in the extended decomposition (11) is identical to the data-generating wage equation (7). 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 affect gender-specific wages. We now demonstrate this point.

4.3. 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., $\bar{x}_m > \bar{x}_f$).

The standard Oaxaca–Blinder wage regression yields a coefficient on the characteristic of male workers of

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

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

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

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

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

see equation (8) for $X = x$. Hence, the estimated explained gap differs from the true one,

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

as long as $\text{cov}(x_m, x_f)/\text{var}(x_m) > -1$ – that is, 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, $\text{cov}(x_m, x_f) > 0$, the standard decomposition understates the explained wage gap, $\widehat{\Delta}|_x < \Delta|_x$, when the career-prioritization channel is dominant (i.e., if $\beta_{2,m} < 0$). In contrast, the spill-over channel being dominant would imply that the standard decomposition overstates the explained wage gap.⁷

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

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

⁷Under 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.

and corresponds to the true explained gap $\Delta|_x$; see equation (8). The estimated unexplained gap is

$$\widehat{\Delta}|_b = \Delta - \widehat{\Delta}|_x = (\beta_{1,m} - \beta_{1,f}) \cdot \bar{x}_f + (\beta_{2,m} - \beta_{2,f}) \cdot \bar{x}_m,$$

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, the inclusion of 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., $\beta_{2,m} < 0$).

5. Empirical analysis

For the empirical analysis, we use data from the Panel Study of Income Dynamics (PSID). The PSID is the most suited US data set for decompositions of the gender wage gap as it has information on actual labor market experience, a key explanatory variable.⁸ 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. Like Blau and Kahn (2017), we use data for the years 1980, 1989, 1998, and 2010.⁹

5.1. Sample selection, explanatory variables, and descriptive statistics

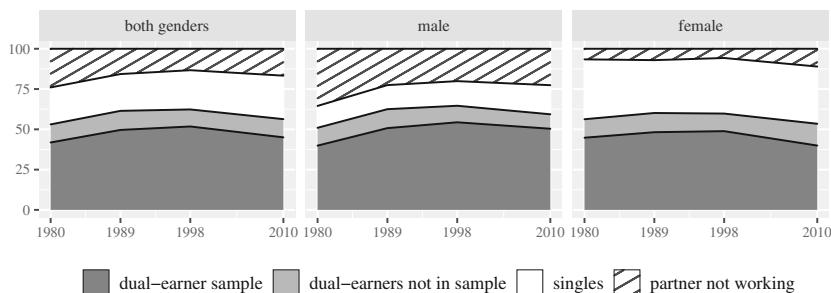
5.1.1. Sample. We start with a sample of full-time workers. Following Blau and Kahn (2017), we select employees aged 25–64 working full-time in the non-farm/non-military sector for at least 26 weeks per year, excluding the self-employed as well as the immigrant and Latino samples.¹⁰ We then select different subsamples of full-time workers, most importantly the subsample of workers living in dual-earner households.¹¹

⁸The PSID is widely used for studying women's wages and labor supply; see, for example, Altug and Miller (1998), Olivetti (2006), Albanesi and Olivetti (2009), Gayle and Golan (2012), Blau and Kahn (2017), and Cortés and Pan (2023).

⁹Earnings in the PSID refer to the previous year. Hence, we use, for example, 1981 data to measure wages in 1980.

¹⁰As is standard, full-time is defined as being employed and working at least 35 hours per week.

¹¹In 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).

Figure 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).

To construct a sample of workers living in dual-earner households, 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, our dual-earner sample contains more men than women, mostly because part-time rates are higher for women.

The left panel of Figure 1 shows the shares of workers in dual-earner households and of single earners within the population of full-time workers. Somewhat more than every second full-time worker is part of a dual-earner couple (the two gray areas) and single earners (the two white areas) constitute slightly less than 50 percent of full-time workers. Within the group of single earners, the share of singles (the area without hatching) increases over time. The middle and right panels of Figure 1 show that, for both genders, workers in dual-earner couples are about 50 percent of all full-time workers. Among single earners, there are only few female workers who have a non-working partner.¹²

Regarding selectivity, we show that our dual-earner sample is similar to the Blau–Kahn sample with respect to trends in the gender wage

¹²Our 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), and 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), and 2,447 (in 2010) women.

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.

5.1.2. 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, and the squares of both variables to account for potentially diminishing returns), 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 Census 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.¹³

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 to what extent 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 the 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 that 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; 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

¹³The 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.

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 childcare and that their distribution within the couple is to a large extent driven by norms (Bertrand et al., 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. We also consider specifications where 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 point of view 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).

5.1.3. Descriptive statistics. The first part of Table 1 shows average log wage rates by gender as well as the gender wage gap for our dual-earner sample (Columns 1–4) as well as for the sample of full-time workers independent of household type used by Blau and Kahn (2017) (Columns 5–7). Both groups 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 moderate.

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.¹⁴ 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 and they are still the minority in the high-paying professional occupations traditionally dominated by men, such as lawyers and doctors. 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 1 also shows that pay-relevant characteristics are positively correlated between spouses in dual-earner couples, supporting the assortative-mating assumption applied in Section 4.¹⁵

5.2. Wage regressions

Before turning to wage-gap decompositions, we briefly consider the results of the wage regressions. Table B.1 in Online Appendix B shows the estimated

¹⁴The underlying categorization of occupations follows Blau and Kahn (2017).

¹⁵The correlation in full-time experience is mostly driven by the high correlation in spouse's age. The conditional correlation is relatively small.

Table 1. Log wages, human capital, and selected job attributes by gender, year, and sample

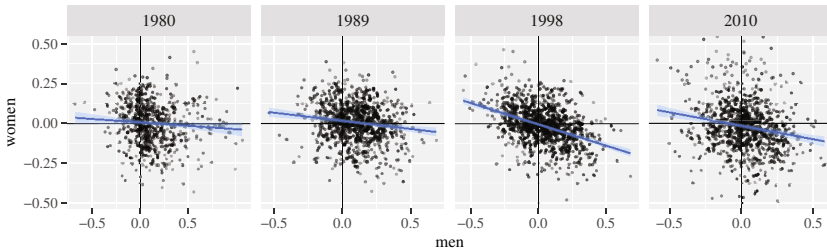
Year	Dual-earner sample				Blau–Kahn sample		
	Men (1)	Women (2)	Difference (3)	Corr(x_i, x_{-i}) (4)	Men (5)	Women (6)	Difference (7)
Log wage rates							
1980	3.08	2.65	0.43	0.36	3.08	2.60	0.48
1989	3.09	2.77	0.33	0.39	3.06	2.76	0.30
1998	3.16	2.89	0.26	0.28	3.11	2.85	0.26
2010	3.29	3.04	0.25	0.37	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
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 percent)							
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
High-pay professional jobs (in percent)							
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

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

coefficients. Here, we present important summary information because most characteristics are non-metric or enter the regressions non-linearly, making the coefficients rather uninformative.

The scatterplots in Figure 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 – that is, if an individual were married to a partner with identical characteristics, $X_{-i} = X_i$. Hence,

Figure 2. Predicted wages relative to potentials

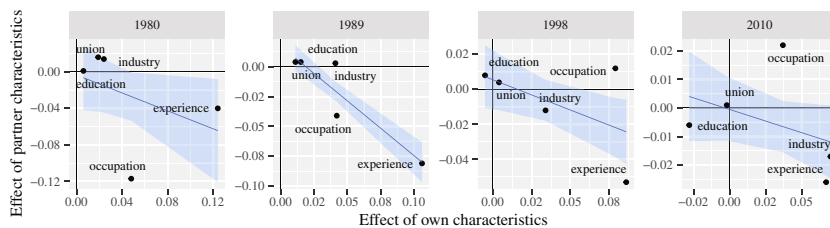


Notes: Differences between predicted log wage, $\widehat{w}_i = \widehat{b}_{1,g(i)}^{ext} X_i + \widehat{b}_{2,g(i)}^{ext} X_{-i}$, and counterfactual log wage, $\widetilde{w}_i = \widehat{b}_{1,g(i)}^{ext} X_i + \widehat{b}_{2,g(i)}^{ext} X_i$, proxying potentials. Each dot represents one couple (male partner on horizontal axis, female partner on vertical axis). The shade of the dot is proportional to family sample weight. The fitted line denotes the 95 percent confidence interval.

we calculate $\widetilde{w}_i = \widehat{b}_{1,g(i)}^{ext} X_i + \widehat{b}_{2,g(i)}^{ext} X_i$. 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 equation (6). This counterfactual wage rate has to be distinguished from the prediction based on the partner’s actual characteristics X_{-i} , $\widehat{w}_i = \widehat{b}_{1,g(i)}^{ext} X_i + \widehat{b}_{2,g(i)}^{ext} X_{-i}$, 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 low relative to his potential, and vice versa. This is a first piece of evidence suggesting the importance of the career-prioritization channel in the data.

Yet, while the predicted deviations from earnings potentials within individual couples shown in Figure 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 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. 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.

The results in Figure 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 are mainly located in the lower-right quadrant. Experience, as the

Figure 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. The horizontal axis separates $\hat{b}_{own,m}^{ext} \cdot (\bar{X}_m - \bar{X}_f)$ into parts related to education, experience, industry, occupation, and union coverage. The vertical axis separates $\hat{b}_{partner,m}^{ext} \cdot (\bar{X}_m - \bar{X}_f)$ analogously. Fitted regression line with \pm one standard error.

most prominent example, satisfies two important conditions. First, men and women differ significantly in this characteristic. Second, 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.¹⁶

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 \bar{w}_i . The results are shown in Table 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. In the early years of our sample, this channel makes up for more than 10 percent of men's wage rates. For women, the effects are smaller, but these estimates should

¹⁶Further corroborating the importance of the career-prioritization channel, our regression results show that a marginal increase in (full-time) experience is associated with an increase in one's own wage but a decline in one's partner's wage. Similarly, men who work in the manufacturing sector earn above-average wages, but men whose wives work in manufacturing earn less than average (conditional on other characteristics). See Table B.1 in Online Appendix B for details.

Table 2. Change in average wages relative to the status quo in a 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, $\tilde{w}_i = \hat{b}_{1,g(i)}^{cxt} X_i + \hat{b}_{2,g(i)}^{cxt} X_i$, by year and gender.

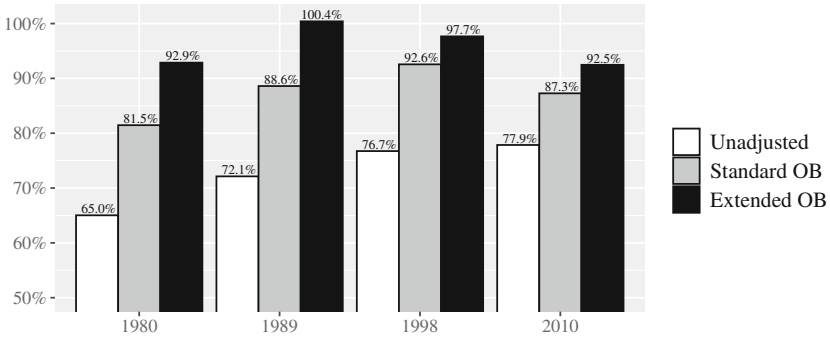
be viewed with caution because of the particularities of female labor supply, such as selection, that are likely to affect the estimated female wage equation more strongly than the one for men. In the later years, differences between actual and counterfactual wages become smaller for men. However, even for the year 2010, where it is 1.6 percent for men and 2.3 percent 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).

5.3. Baseline decomposition

5.3.1. Baseline results. Figure 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 $\hat{\Delta}|_b$; hence, the level of the gap in log points can (approximately) be seen in the figure as the difference between the bars and 100 percent. 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, that is, 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 as men's (i.e., if they had the same coefficients as men). The white bars show the unadjusted wage ratios, which 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 gap, as discussed by Blau and Kahn (2017). However, the adjusted wage ratio stagnates at around 90 percent from 1989 on. Put differently, a gap of roughly 10 percentage points, which corresponds

Figure 4. Comparison of the 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 the raw gender wage gap; see equation (8). Gray bars show $1/\exp((\widehat{\Delta}|_b)^{std})$, where $(\widehat{\Delta}|_b)^{std}$ is the unexplained wage gap of standard decomposition; see equation (10). Black bars show $1/\exp((\widehat{\Delta}|_b)^{ext})$, where $(\widehat{\Delta}|_b)^{ext}$ is the unexplained wage gap of extended decomposition; see equation (12).

to between one-third and three-fifths of the raw gap, remains unexplained by a standard decomposition.¹⁷

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 decomposition explains 100 percent 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 us to explain a substantially larger part of the gender wage gap.

Figure 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 percent) declines substantially over time. One possible interpretation is that the closure of the wage gap between 1980 and 2010 might, to a discernible extent, be attributed to declining discrimination. This interpretation, however, is not supported by our extended Oaxaca–Blinder

¹⁷Note 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 percent, 92.4 percent, 91.4 percent, and 82.1 percent, 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 the selectivity of the dual-earner sample.

decomposition, which delivers a roughly constant unexplained gender gap amounting to about 7 percentage points in both 1980 and 2010.¹⁸

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 non-cognitive 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.

5.4. Sensitivity

We have performed a number of sensitivity checks to corroborate the robustness of our main results. Table 3 summarizes the explained wage gaps $\Delta|_X$ 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.

5.4.1. Sample. As alternative samples, we consider a narrower age range (Row 2) as well as a sample that, compared with our baseline sample of dual earners working full-time and full-year, also includes part-time (Row 3) and part-year (Row 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.

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

¹⁸Blau and Kahn (2006) have studied 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: here also, 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 the presence of continuing convergence of the covariates.

Table 3. Sensitivity analysis

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

Notes: Explained wage gaps $\widehat{\Delta}|_X$ in different specifications of standard and extended decomposition. Row 1 repeats baseline results. Rows 2–5: sample changed as indicated relative to baseline. Rows 6–9: explanatory variables extended as indicated relative to baseline. Row 10: structural equation model where both partners' wages depend on latent earnings potentials of both partners, which are decomposed into education, experience, job information, and other.

women might 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 the fact 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 observed. 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 offered 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 occupation and industry from 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 Row 5 of Table 3. Also in the sample including non-working women, our extended approach assigns considerably larger pay differences to observables than the standard approach.

5.4.3. Linearity. A potential shortcoming of the Oaxaca–Blinder approach is its linearity assumption, and non-parametric wage equations have been estimated as alternatives (DiNardo et al., 1996; Frölich, 2007; Mora, 2008; Ňopo, 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). Row 6 in Table 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 et al., 2017). The results in Row 7 of Table 3 refer to a specification where we included interaction terms of years of schooling with years of full- and part-time experience. In Row 8, we interact education and union status to account for union wage premia differing along the skill distribution. In Row 9, we interact 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.

5.4.4. 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 such as 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 the men's wage equation and, on the other hand, making the analysis subject to biases stemming from estimating the women's wage equation. For comparability to the literature, we chose to estimate only the 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. Row 10 of Table 3 shows the results of a wage-gap decomposition based on the estimates from this specification. Here, we also find our main result confirmed: explained gaps are larger for extended decompositions that take into account partner characteristics.¹⁹

5.5. Implications for households with a single earner

Given that the model mechanism that leads to the bias in a standard Oaxaca–Blinder decomposition is absent for bachelor households and less important for 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 5 shows results for singles (individuals with no partner, neither married nor cohabiting, left panel) and single earners (individuals who are the sole earner in their household independent of marital or cohabitation status, right panel).²⁰ The left panel 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 decomposition suggests in a sample of dual-earner couples or in a sample of all workers. The right panel reveals a similar pattern for single earners in general. Also, the standard decomposition explains large shares of the gender wage gap, ranging to close to 100 percent.

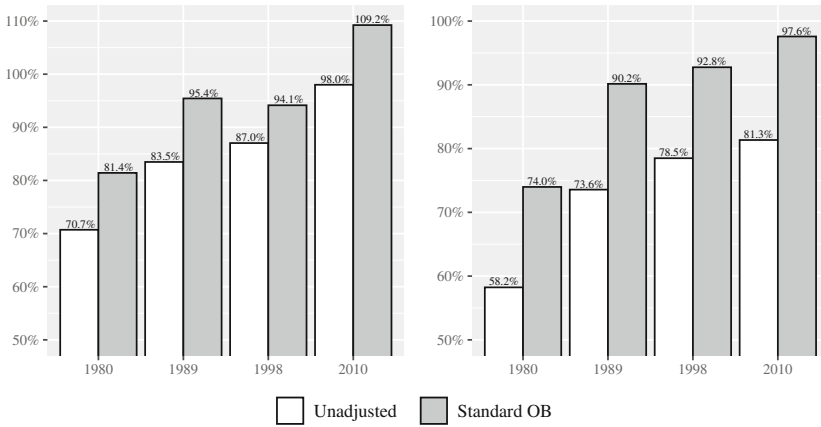
5.6. Wage effect of partner's experience and role of children

Our results show that experience is a key characteristic for explaining the gender wage gap. Especially in the case of work experience, however, one

¹⁹With all caution due to the challenges associated with estimating the 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.

²⁰The 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 1,109 (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.

Figure 5. Standard Oaxaca–Blinder (OB) decomposition in a sample of singles (left panel) and single earners (right panel): log female-to-male wage ratio, unadjusted and adjusted for covariates



Notes: White bars show $1/\exp(\Delta)$, where Δ is the raw gender wage gap; see equation (8). Gray bars show $1/\exp((\widehat{\Delta}|_b)^{std})$, where $(\widehat{\Delta}|_b)^{std}$ is the unexplained wage gap of the standard decomposition; see equation (10).

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 with high incomes due to, for example, the unobserved ability of the husband, and thus a high wage for him, might 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 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 the number and ages of children in the household to predict full-time work experience. We then used these predictions instead of the actual 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 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.²¹

²¹As information on siblings is not available in 1981, we do not perform these estimations for this year.

Table 4. Average marginal effects of an additional year of full-time experience (own and their partners') on men's log wages

	1989	1998	2010
Panel A. Model with observed partner's experience			
Own experience	0.017 (0.002)	0.010 (0.002)	0.014 (0.002)
Partner's experience	-0.010 (0.003)	-0.007 (0.003)	-0.003 (0.003)
Panel B. Model with predicted partner's experience based on children			
Own experience	0.017 (0.002)	0.009 (0.002)	0.013 (0.003)
Partner's predicted experience	-0.024 (0.013)	-0.021 (0.011)	-0.014 (0.007)
Panel C. Model with predicted partner's experience based on siblings			
Own experience	0.018 (0.002)	0.007 (0.002)	0.012 (0.003)
Partner's predicted experience	-0.017 (0.008)	-0.012 (0.006)	-0.014 (0.005)

Notes: Panel A shows results from the baseline specification of the extended wage equation (with observed experience). Panel B uses predicted full-time and part-time experience based on number of children, interacted with individual's age and education. Panel C uses predicted full-time and part-time experience based on number of own and partner's siblings, interacted with age and education. Standard errors are given in parentheses.

Table 4 shows the marginal effects on men's log wages of an additional year of work experience (their own or their partner's). Panel A shows the effects implied by our baseline regression, which uses actual rather than predicted experience. Predicted experience measures for wives are used in Panels B and C. As is well known in the literature, (own) work experience is a quantitatively significant wage determinant. In our sample, an additional year of work experience is associated with a 1–2 percent higher wage, on average. Regarding partner experience, 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.

These evaluations also help us to understand the role of children in wage-gap decompositions. Because the number of children in family households is the same for both the 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.

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 with 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. An extended decomposition approach that includes partner characteristics accounts for the role of the family and corrects the bias successfully. In US 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. 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.

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Supporting information

Additional supporting information can be found online in the supporting information section at the end of the article.

Online appendix Replication package

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