Gender Gaps in Pay and Inter-Firm Mobility: The Role of Relative Earnings Within Households

Christian Bredemeier*

University of Wuppertal and IZA

This version: September 2025

Abstract

The gender gap in inter-firm mobility, an important contributor to the gender pay gap, remains largely unexplained. In a structural workplace-choice model, I show that women's lower mobility arises from their secondary-earner role in most household, which makes non-pay aspects of women's workplaces more important for households. I provide empirical evidence for this explanation by documenting that quits respond less strongly to wages when individuals contribute smaller shares to household earnings. Gender differences in mobility largely vanish once relative earnings are accounted for. Model simulations show that ignoring the earner-role mechanism yields substantial biases in wage-gap decompositions and policy predictions.

Keywords: Gender gaps, job mobility, discrimination, monopsony

JEL classification: J16, J62, J71, J42

1 Introduction

The gender pay gap is both a major societal concern and a regular focus of study for labor economists (Bertrand et al. 2019; Biasi and Sarsons 2021; Binder et al. 2024; Cullen and Perez-Truglia 2023; Goldin et al. 2017). Although it has narrowed considerably over the past 50 years, a gap of roughly 20% persists in many developed economies, and a large share cannot be explained by observable characteristics (Blau and Kahn 2017).

*Mail: bredemeier@uni-wuppertal.de. I thank Tobias Föll, Falko Jüßen, Michael Krause, David Ong, Roland Winkler, seminar participants at Bielefeld, Cologne, Jinan, Munich (LMU), Witwatersrand, Wuppertal, RWI, and IZA as well as conference participants at Computation in Economics and Finance, Econometric Society, Economic Association of South Africa, German Economic Association, French Economic Association, and Royal Economic Society for many helpful comments and suggestions. After completing the full manuscript, I used OpenAI's GPT-5 language model to assist in improving phrasing and clarity. I critically reviewed and revised all AI-generated text, and all ideas, arguments, and conclusions are my own.

The gender gap in inter-firm mobility is an important contributor to the unexplained gender wage gap, as it allows firms to exercise monopsonistic discrimination against women. It is a well-established empirical fact that firms hold substantial market power in the labor market because workers are imperfectly mobile between them, which allows firms to compress wages (Berger et al. 2022; Dube et al. 2020; Langella and Manning 2021; Lamadon et al. 2022; Yeh et al. 2022). Further, women exhibit even lower inter-firm mobility than men, in that their workplace choices are less responsive to wage differences between firms (Ransom and Oaxaca 2010; Webber 2016; Mas and Pallais 2017; Wiswall and Zafar 2017).[1] These choices are in turn more strongly affected by non-pay job characteristics such as collegiality, flexibility, social contribution, tasks, or commuting time (Niederle and Vesterlund 2007; Grove et al. 2011; Goldin 2014; Flory et al. 2014; Kuhn and Villeval 2015; Goldin and Katz 2016; Gomes and Kuehn 2025; Redmond and McGuinness 2020; Gelblum 2020; Xiao 2024; Liu and Su 2022), though the key point for wage determination are responses to pay differences. Firms can exploit women's lower mobility to pay them less than men (for evidence, see Ransom and Oaxaca, 2010, and Félix and Portugal, 2017).[2] Resulting within-firm gender gaps in pay can be substantial. Surveying the literature, Hirsch (2016) estimates that 40–65% of the unexplained gender gap can be attributed to this mechanism. Yet the causes of gender differences in the wage sensitivity of employer choices remain poorly understood (Hirsch, 2016, page 8).

In this paper, I provide a theoretical explanation for the gender gap in inter-firm mobility, present direct empirical evidence for it, and assess its quantitative implications for the gender pay gap. My explanation is based on joint household decision-making. While the literature

[1] For non-U.S. evidence, see, e.g., Barth and Dale-Olsen (2009), Hirsch et al. (2010), Booth and Katic (2011), Sulis (2011), Redmond and McGuinness (2019), Detilleux and Deschacht (2024), and Sánchez et al. (2022).

[2] In the U.S. and many other countries, this occurs despite legal prohibitions against gender-based pay discrimination, through lower promotion rates (Bosquet et al. 2019; Gobillon et al. 2015; Pekkarinen and Vartiainen 2006; Booth et al. 2003), less frequent raises (Babcock and Laschever 2009; Artz et al. 2018), assignment to lower-paying jobs (Ransom and Oaxaca, 2005) or tasks (Babcock et al., 2017), and reduced discretionary compensation (e.g., Grund, 2015). The gender gap in inter-firm mobility implies that firms can treat women in these ways without risking the loss of many female workers. Further, it implies that women leave low-pay firms at lower rates than men such that in the long run men sort to better-paying firms (Card et al. 2018; Bayard et al. 2003).

has increasingly recognized that labor supply should be considered as a joint decision of the family (Doepke and Tertilt 2016), most papers focus on the choice of whether or how much to work.[3] I extend this notion to the choice of where to work and whether to change jobs.[4] In my model, spouses jointly weigh pay and non-pay characteristics when selecting jobs.

I argue that pay is less important for women's workplace choices, not primarily because they intrinsically value non-pay characteristics more, but because their earnings are less critical to household income. In dual-earner households, spouses often differ in earnings potential, making relative changes more relevant when they relate to the higher-earning spouse. In turn, this makes non-pay characteristics more important relative to pay when deciding where the other spouse should work. I formalize these relations in a model of workers' choices between heterogeneous workplaces that extends the frameworks of Card et al. (2018) and Wiswall and Zafar (2017) by incorporating dual-earner couples. The model links a worker's wage sensitivity to their share of household earnings, so that the gender gap in inter-firm mobility reflects differences in earner roles.[5]

[3]There is strong empirical evidence (e.g., Cherchye et al., 2012, Donni and Moreau, 2007) that labor supply is a joint decision of spouses and understanding them as such has been helpful to better explain phenomena such as consumption insurance against wage-rate shocks (e.g., Blundell et al., 2016, Autor et al., 2019, Wu and Krueger, 2021) and the determinants of female labor supply (e.g., Guner et al., 2012a, 2012b, Bick, 2016, Bick and Fuchs-Schündeln, 2017, 2018) or normative issues such as optimal unemployment insurance (Ortigueira and Siassi, 2013, Choi and Valladares-Esteban, 2020) or pension systems (Nishiyama, 2019, Groneck and Wallenius, 2020).

[4]The joint-search literature studies the joint decisions of households whether a spouse searches for a job and when to accept a job offer. As is common in the search-and-matching framework, most papers (e.g., Mankart and Oikonomou, 2017, Wang, 2019) in this literature model heterogeneity of workers and jobs and the matching between the two as embedded in a black-box stochastic arrival process of matches. Hence, a job and a worker can fit each other (a match) or not and this is determined exogenously while, in my model, I study the decision of households how to balance pay and non-pay characteristics of a job. Guler et al. (2012) have an explicit non-pay dimension of jobs, their location. In this dimension, couple households have a clear incentive to search for jobs for husband and wife which are at similar locations. Importantly, the costs of different job locations are borne equally by both spouses. I understand non-pay job characteristics more broadly and take seriously the issue that a household may pick jobs with differently likable job characteristics for husband and wife.

[5]In line with my explanation based on relative earnings within households, Webber (2016) documents that the gap in inter-firm mobility is larger between married men and married women than between singles of both genders, for whom my channel is absent. A similarly supportive finding is reported by Ransom and Oaxaca (2010) who document that the gender gap in inter-firm mobility has become smaller over time, as has the gender earnings gap. Both observations are in line with my channel while the alternative explanation of intrinsic gender differences in the importance of non-pay job characteristics would imply that the gender gap in inter-firm mobility should be rather constant across the population and over time. In a decomposition, Detilleux and Deschacht (2024) find that only a fourth of the gender gap in the wage sensitivity of separations can be linked to differences in preferences such as risk aversion and patience.

As a testable prediction, my model implies that the wage sensitivity of quits is stronger for people contributing larger shares to household earnings. I test this prediction empirically in quit regressions where I include the share of contributed earnings and its interaction with the wage rate. The results strongly support my theory. I find a significant, quantitatively important, and robust effect of intra-household relative earnings on the wage sensitivity of quits, in the expected direction. A ten-percentage-point increase in the share one contributes to household earnings raises mobility between firms by about 10%. Once I take household earner roles into account, remaining gender differences in the wage sensitivity of quits are small and statistically insignificant. This implies that men and women would be very similar in terms of inter-firm mobility if they contributed equally to household earnings.

My results suggest a feedback loop between gender gaps in pay and inter-firm mobility. For instance, if men's higher experience leads firms to pay them more, households respond by supplying female labor less elastically, which allows firms to further suppress women's wages. Similar mechanisms operate for differences in labor supply or non-pay job preferences. I provide a quantitative model assessment that shows that the loop between gender gaps in pay and inter-firm mobility amplifies the effects on the gender wage gap of changes in exogenous gender differences or gender-specific policy changes by about 30%.

Accounting for this feedback loop means that smaller exogenous gender differences are needed to generate observed outcome gaps, and a larger fraction of the gaps can be explained endogenously compared to models that abstract from the impact of household earner roles in determining intra-firm mobility. My quantitative analysis shows that considering household earner roles reduces the non-pay preference differences needed to match observed gaps by a factor of five and raises the share of the wage gap attributed to labor-demand factors, such as experience, by roughly one-third.

The amplification mechanism proposed in this paper complements other recently developed mechanisms showing how household decisions can amplify gender differences. 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 to allow searching for high wage jobs for men.[6] Location choices of dual-earner couples amplify pay differences between members when they are primarily aimed at fostering the primary earner's career (Averkamp et al., 2024) and improving women's earnings opportunities reduce the number of male-driven household moves (Braun et al., 2021), thereby amplifying the effect on the wage gap. Bredemeier et al. (2025) present empirical evidence on job satisfaction by gender and role in the household that is consistent with secondary earners tending to choose jobs that offer lower wages but constitute better matches to individual preferences, a behavior that also implies amplification of pay differences between genders.

The remainder of this paper is organized as follows. Section 2 derives the main theoretical results analytically. Section 3 presents the empirical analysis. Section 4 discusses the quantitative model evaluations. Section 5 concludes.

2 Basic model

I first consider a simple model with the minimal set of ingredients needed to illustrate the basic mechanism. To keep the basic model as simple and transparent as possible, I start with a set-up like the ones used by Card et al. (2018) and Wiswall and Zafar (2017), including only the monopsonistic friction, and add dual-earner couples. A dynamic monopsony representation with identical steady-state results can be found in Web Appendix A.2 presents. Web Appendix A.1 focuses on quit decisions by workers. I address search costs in Web Appendix A.3. Several additional features (endogenous hours, segregated labor markets, within-gender inequality, singles, gender differences in market-level elasticities, home production, and firm entry) are addressed in the quantitative analysis in Section 4. Some modeling choices are shared by Bredemeier et al. (2025) who embed monopsonistic labor-markets à la Card et al. (2018) into a macroeconomic DSGE business-cycle model.

[6] 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 reservation wages of partners of highly educated individuals are compressed through increased willingness to bear risk and the partner's comparative advantage in search.

The basic model can be described as follows. There is a finite number V of firms and two types of workers, male and female workers who live together in couple households and make workplace choices jointly. Firms differ in non-pay characteristics (such as location, the tasks to be performed, the work climate, and the flexibility or predictability of a job) over which workers have heterogeneous preferences.[7] This gives a firm local monopsony power over the workers who like its characteristics. Firms cannot observe an individual worker's job preferences which rules out wage discrimination against individual workers. Each firm posts a pair of group-specific wage rates, which workers can observe at no cost. Based on these wage rates, households choose a firm for each worker and firms hire any worker who is willing to accept the offered wage rate.

The model allows for potential gender differences in three exogenous dimensions, preference differences regarding the importance of non-pay job characteristics, differences in the marginal revenue product of a worker, and differences in hours worked. As discussed in the introduction, I propose a mechanism that reduces the amount of exogenous gender differences to be fed into a model in order to rationalize observed gender differences in labor-market outcomes. I do not aim at explaining the deep roots of these differences. My model still needs a trigger to set in motion the amplifying mechanisms I highlight. Yet, it is a key implication of the model that rather small triggers can suffice to generate substantial gender differences in outcomes.

2.1 Households

There are two members in each household, a woman indexed by f and a man indexed by m. Jointly, they choose consumption c, and workplaces k_f, k_m to maximize

$$u = \log c + \frac{1}{\gamma_f} \cdot \kappa_f \left(k_f\right) + \frac{1}{\gamma_m} \cdot \kappa_m \left(k_m\right), \tag{1}$$

[7] Manning (2011) argues that these non-pay dimensions of a job are the key obstacles to finding a suitable employer and are hence key for understanding what is meant by search on the labor market. Sullivan and To (2014) show empirically that such non-pay characteristics play a major role for workers' job search behavior.

where the $\kappa_g(k_g)$, with $g = f, m$ indexing gender, describe utility from non-pay characteristics of the chosen firm.[8] I assume that the additional utility agents achieve at the different potential employers, $\kappa_g(v)$, are independent draws from a type-I extreme value distribution with scale parameter $1/V$. The exogenous utility weights γ_m and γ_f measure the (inverse) importance of non-pay job characteristics to men and women, respectively.[9] I allow these weights to be gender-specific but the qualitative results will not hinge on this. In fact, the quantitative evaluations show that the weights γ_f and γ_m are rather similar and that most of the gender gap in inter-firm mobility arises endogenously in the model.

To induce worker flows between firms, I assume that each period a fraction θ of workers is randomly selected and randomly assigned new preferences over firms' non-pay job characteristics, with no correlation to past preferences. One interpretation of this change in a worker's preferred job characteristics is a change in the family situation such as a child birth, a child moving out of the household, a parent needing care, or the household moving, i.e., changing its geographical location for exogenous reasons such as inheriting a house. Yet, the model does not feature any persistence in job choices and no uncertainty around future wages and earnings, it can thus be solved period by period.

Households act subject to the budget constraint

$$c = w_f(k_f)\, h_f + w_m(k_m)\, h_m,$$

where $w_g(k_g)$ is the wage rate offered to workers of gender g by the chosen firm k_g and h_g are hours worked by household member g. Hours are exogenous in the basic model but will be endogenous in the quantitative model in Section 4.

[8] I abstract from complementarities between the non-pay characteristics of spouses' jobs in utility. An easy way to introduce such complementarities would be to let the weight γ_g depend on realized non-pay job utility of the partner. However, the realized non-pay utilities are a constant in the symmetric equilibrium. Hence, such an extension would only affect worker's responses to unilateral (off-equilibrium) wage changes by firms in couples where both spouses work for the same firm. Following the literature, I assume that the number of firms is large which implies that the share of such couples is minimal.

[9] I scale the distribution of taste shifters κ by the number of firms, reflecting that, in markets where more firms are active, differences between any two firms are smaller and thus can be expected to matter less. This scaling is innocuous in the basic model considered here but affects the interpretation of the quantitative model (see Section 4) and matters in an extension where I consider firm entry which makes V endogenous.

Workplace choice. Using standard logit solution techniques, one can easily determine the share of workers working for a firm j among those workers whose spouses work for another firm i. For each gender g, this share is given by

$$\frac{\exp\left(\gamma_g V \log\left(w_{j,g}h_g + w_{i,-g}h_{-g}\right)\right)}{\sum_{p=1}^{V} \exp\left(\gamma_g V \log\left(w_{p,g}h_g + w_{i,-g}h_{-g}\right)\right)}, \tag{2}$$

where $-g$ denotes the other gender. Consequently, the total mass of workers of gender g working for firm j is[10]

$$n_{j,g} = \sum_{i=1}^{V} n_{i,-g} \frac{\exp\left(\gamma_g V \log\left(w_{j,g}h_g + w_{i,-g}h_{-g}\right)\right)}{\sum_{p=1}^{V} \exp\left(\gamma_g V \log\left(w_{p,g}h_g + w_{i,-g}h_{-g}\right)\right)} \tag{3}$$

As Card et al. (2018), I assume that strategic interaction between firms in wage setting is negligible and consider a symmetric equilibrium.[11] This implies that the slope of the labor-supply curve faced by an individual firm is

$$\begin{aligned}\frac{\partial n_{j,g}}{\partial w_{j,g}} &= \sum_{i=1}^{V} n_{i,-g} \frac{\exp\left(\gamma_g V \log\left(w_{j,g}h_g + w_{-g}h_{-g}\right)\right)}{\sum_{p=1}^{V} \exp\left(\gamma_g V \log\left(w_{p,g}h_g + w_{-g}h_{-g}\right)\right)} \cdot \gamma_g \cdot V \cdot h_g \cdot \frac{1}{w_{j,g}h_g + w_{-g}h_{-g}} \\ &= n_{j,g} \cdot \gamma_g \cdot V \cdot h_g \cdot \frac{1}{w_{j,g}h_{j,g} + w_{-g}h_{-g}}.\end{aligned}$$

It follows that the elasticity of labor supplied by workers of group g to an individual firm is

$$\eta_g = \frac{\partial n_{j,g}}{\partial w_{j,g}} \cdot \frac{w_{j,g}}{n_{j,g}} = \gamma_g \cdot V \cdot \frac{w_g \cdot h_g}{w_g h_g + w_{-g}h_{-g}}. \tag{4}$$

This elasticity is the key measure of inter-firm mobility as it determines how strongly firms can pay workers below their marginal revenue product, see Section 2.2 below.[12]

Intuitively, a worker who intrinsically does not put much weight on non-pay job attributes (large γ) has a high sensitivity of job choices to pay. Inter-firm mobility further depends on

[10] To obtain the total number of workers of gender g at firm i, (2) is multiplied with the number of workers of the other gender at firm i and then summed up over all firms i.

[11] Note that this assumption affects men and women symmetrically.

[12] Web Appendix A.2 presents an alternative derivation of the firm-level labor-supply elasticity that focuses on worker's quit decisions in response to wage cuts by their employers. In Web Appendix A.3, I show that accounting for search costs would alter the result above only through a uniform re-scaling of the parameters γ_m and γ_f.

the number of firms V as it determines the distance of a firm to its most similar competitor in terms of job characteristics. Finally and most importantly, inter-firm mobility depends on the contributed share to household earnings, $w_g h_g/(w_g h_g + w_{-g}h_{-g})$. Earnings of an individual who is married to a partner with high earnings are of little importance to the household. In the limit, this individual would simply work for the firm that he or she likes best and the reaction to this (or another) firm's pay would be minimal.

Using (4), the gender gap in inter-firm mobility is

$$\Delta\eta = \log \eta_m - \log \eta_f = \Delta\gamma + \Delta w + \Delta h. \tag{5}$$

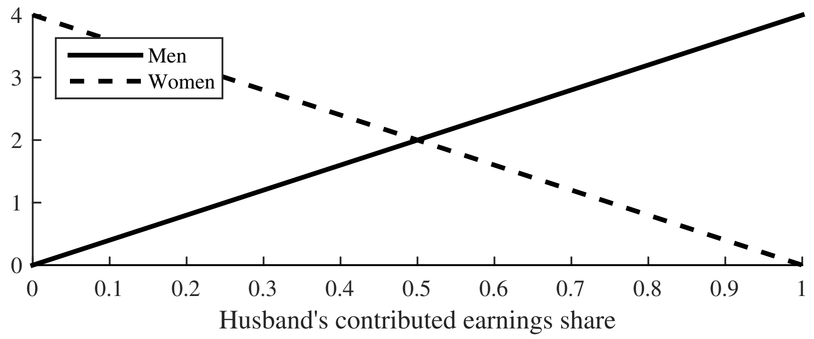
The mobility gap thus reflects both, gender differences in exogenous aspects determining the importance of job characteristics ($\Delta\gamma$) and differences stemming from roles in the household (Δw and Δh). An example for the former can be differences in risk aversion (e.g., Croson and Gneezy, 2009, Iriberri and Rey Biel, 2021) which can lead women to dislike uncertain work environments more strongly (Heinz et al. 2016).[13] An example for the latter type may be working night shifts which presumably men and women both dislike but households may choose to accept this unlikable job attribute in exchange for higher pay when determining the workplace for the primary earner but not when determining the one for the secondary earner. My following empirical and quantitative results suggest that gender differences in inter-firm mobility are driven rather by the latter than the former aspect.[14]

Figure 1 illustrates the elasticity of labor supply to individual firms as a function of relative earnings within the household, i.e., the share contributed to household earnings by the husband. For the figure, I abstract from gender differences in the preference parameter γ, hence men and women intrinsically care the same about job characteristics. Consequently, there are no intrinsic gender differences in terms of inter-firm mobility which is reflected

[13] Other examples include differences in self-confidence (Bordalo et al. 2019), attraction to high stakes (Azmat et al. 2016), bargaining (Hernandez-Arenaz and Iriberri 2018), or self-promotion (Exley and Kessler 2022).

[14] Manning and Saidi (2010) document that differences in *preferences* for competitive work environments contribute only little to the UK gender wage gap. McGee et al. (2015) report similar evidence for the US.

Figure 1: Model-predicted elasticity of labor supply to individual firms as a function of the husband's contributed share to household earnings.



Notes: Example for $\gamma_f = \gamma_m = 0.4$ and $V = 10$.

in the symmetry of the two lines. If men and women contributed equally to household earnings, the model would predict them to be equally mobile between firms. However, in situations where their earnings differ, the model predicts the primary earner to be more mobile between firms. Empirically, most couples are in the right part of the figure where men earn more and are more mobile between firms.

2.2 Firms

Firms produce output with labor of both genders. Output depends on total hours work by gender at this firm, the product of the mass of workers attracted by the firm, $n_{j,g}$, and hours worked per worker, h_g. Firms choose wage offers to women and men to maximize

$$a_{j,f}n_{j,f}h_f + a_{j,m}n_{j,m}h_m - w_{j,f}n_{j,f}h_f - w_{j,m}n_{j,m}h_m$$

where $a_{j,g}$ is the marginal revenue product of workers of gender g at firm j, subject to the labor-supply schedule they face from workers of both genders (described by (3) for $g = f, m$). Marginal revenue products have a firm-specific component and a gender specific component, $\log a_{j,g} = \log \alpha_j + \log \alpha_g$. I denote the average marginal revenue product of workers of gender g as a_g. Gender differences in a_g can stem from differences in gender-specific components or from gender-specific matchings of workers to firms (i.e., workers of a specific gender could work at more productive firms at different rates). To keep the exposition simple, I consider in the basic model the case where the variance of firm-specific components in marginal revenue products is arbitrarily small, $\text{var}(\alpha_j) \to 0$, such that the equilibrium is reasonably approximated by the symmetric equilibrium between identical firms.

It is profit-maximizing for firms to offer a given group of workers wage rates at a mark-down below that group's marginal revenue product with the mark-down depending on the group's elasticity of labor supply to the individual firm. The first-order condition for $w_{j,g}$ is $a_g h_g \cdot \partial n_{j,g}/\partial w_{j,g} - n_{j,g} h_g - w_{j,g} h_g \cdot \partial n_{j,g}/\partial w_{j,g} = 0$ and implies

$$w_{j,g} = a_g \cdot \frac{\eta_g}{1+\eta_g}. \tag{6}$$

Hence, the gender wage gap in a symmetric equilibrium is, up to first order, given by

$$\Delta w = \Delta a + \frac{1}{1+\overline{\eta}} \Delta \eta \tag{7}$$

where $\overline{\eta}$ is the average firm-level labor-supply elasticity. (7) uses a first-order Taylor approximation around $\eta_m = \eta_f = \overline{\eta}$. Hence, the wage gap is a combination of gender differences in marginal revenue products and monopsonistic discrimination against women.[15]

2.3 Equilibrium gender gaps

In the model, there is a circular relation between gender gaps in pay and inter-firm mobility. On the one hand, deriving the wage sensitivity of workplace choices from a household labor-supply problem implies that the gender gap in inter-firm mobility depends on the gender earnings gap, see (5). On the other hand, firms' monopsonistic wage setting induces the gender wage gap to be affected by the gender gap in inter-firm mobility, see (7). Solving the

[15] Note that Δa should be understood as reflecting all factors outside of the model that lead to a lower contribution of female workers to firm revenue such as differences in physical strength but also the assignment of men and women to different tasks (Babcock et al. 2017) or their segregation on industries with different market power of firms on the goods market. From a human capital perspective, Δa may also reflect foregone experience accumulation during career interruptions, which occur more frequently for women, or lower training investment by firms anticipating such interruptions. A certain part of Δa can also be interpreted as taste-based, or Beckerian, discrimination since discriminatory firms may survive on monopsonistic labor markets. With this broad understanding of Δa, I will refer to it as the gender gap in labor-demand factors.

system of (5) and (7) gives the equilibrium gender gaps as

$$\Delta w = \frac{\overline{\eta}+1}{\overline{\eta}} \cdot \Delta a + \frac{1}{\overline{\eta}} \cdot \Delta \gamma + \frac{1}{\overline{\eta}} \cdot \Delta h \tag{8}$$

and

$$\Delta \eta = \frac{\overline{\eta}+1}{\overline{\eta}} \cdot \Delta a + \frac{\overline{\eta}+1}{\overline{\eta}} \cdot \Delta \gamma + \frac{\overline{\eta}+1}{\overline{\eta}} \cdot \Delta h. \tag{9}$$

The two equations above illustrate the feedback loop between gender gaps in pay and inter-firm mobility. On the one hand, firms' monopsonistic wage setting induces the gender wage gap to be affected by the gender gap in inter-firm mobility, see (8). On the other hand, deriving the wage sensitivity of workplace choices from a household labor-supply problem implies that the gender gap in inter-firm mobility depends on the earnings gap, see (9).

2.4 A reference model without couples

To shut off the endogeneity in job mobility generated by couple decision-making, I now consider a version of my model where every worker lives alone and seeks to maximize

$$u_g = \log c_g + \frac{1}{\gamma_g} \cdot \kappa_g (k_g)$$

subject to

$$c_g = w_g (k_g) h_g.$$

It is straightforward to show that, in this model version,

$$\eta_g = \gamma_g \cdot V \cdot \frac{w_g h_g}{c_g} = \gamma_g \cdot V. \tag{10}$$

Given group-specific values of the elasticity of labor supply to individual firms, firms behave as in the full model. Accordingly, wage offers and the gender wage gap are described by equations (6) and (7) as well. Hence, equilibrium gender gaps in pay and inter-firm mobility are, in this version, given by

$$\Delta w = \Delta a + \frac{\overline{\gamma}}{2} \cdot \Delta\gamma, \tag{11}$$

$$\Delta\eta = \Delta\gamma \tag{12}$$

Also here, the gender wage gap is a combination of gender differences in marginal revenue products and monopsonistic discrimination against women due to the gender mobility gap. The latter, however, is here determined by exogenous preference differences alone.

2.5 Main implications

Here, I derive the main implications of the model analytically to strengthen intuitions. In Section 4, I quantify these results in a larger model that I solve numerically.

Amplification. Endogenizing inter-firm mobility through modelling joint workplace choices of dual-earner couples leads to an amplification of changes in exogenous gender gaps. For convenience, the upper part of Table 1 repeats the equilibrium gender gaps in both model versions. Comparing how the exogenous gaps affect the endogenous gaps in both models reveals the amplification in the full model: The effect of a change in any exogenous gender gap, Δa, $\Delta\gamma$, or Δh, on the endogenous gender gaps, Δw and $\Delta\eta$, is stronger in the full model than in the reference model. For example, a one-percent change in Δa translates into a one-percent change in the wage gap Δw in the reference model but changes the wage gap by $(\eta + 1)/\eta > 1$ percent in the full model.

The intuition behind this result lies in the feedback loop between gender gaps in pay and inter-firm mobility. For example, a reduction in gender differences in labor-demand factors (such as increases in women's labor-market experience induced by policies facilitating the return to work after maternity leaves or growing social acceptance of working mothers) decreases the wage gap directly and, thus, also increases the importance of women's earnings for households. This makes the choice of women's workplaces more sensitive to pay, i.e., women more mobile between firms. This reduces firms' ability to suppress women's wage rates and thus exerts a second, indirect effect on the wage gap. This in turn again affects the mobility gap and so on.[16] A model that overlooks this amplification delivers too weak predictions regarding the effects of changes in policies and social norms.

Role of preference differences. Accounting for endogenous inter-firm mobility allows reducing the amount of gender differences in preferences required to rationalize observed gender gaps. The middle block of Table 1 shows the required exogenous gaps the two model versions need to match given observations Δw and $\Delta\eta$. While the required value for Δa is the same for both versions, the full model requires smaller gender differences in preferences for job characteristics than does the reference model (as long as $\Delta w + \Delta h > 0$). The full model generates a gender mobility gap, $\Delta\eta > 0$, even without any gender differences in preferences, $\Delta\gamma = 0$, while the reference model strictly requires such differences, $\Delta\gamma > 0$.

Decomposition of gender gaps. I will now analyze how important, according to the models, the three dimensions of exogenous differences between men and women are for explaining the endogenous gender gaps in pay and inter-firm mobility. Using the required gaps from the middle block of Table 1 in the equilibrium gender gaps from the upper part, I obtain the percentage contributions of the different exogenous gender gaps for the endogenous gaps. For example, I calculate the contribution of labor-demand differences for the gender gap, $\Delta w|_{\Delta a}/\Delta w$, by determining the gender wage gap when the other two exogenous gender gaps are counterfactually set to zero. The results of this decomposition exercise are summarized in the bottom block of Table 1.

The results above show that endogenizing inter-firm mobility through couple decision-making increases the importance of labor-demand factors and reduces the importance of preference differences for understanding gender gaps in pay and inter-firm mobility.[17] Put

[16] Similarly, a reduction in the importance of non-pay characteristics of women's workplaces makes women become more mobile between firms directly. The resulting loss in firms' market power vis-à-vis women reduces the wage gap which then again influences the mobility gap and so on.

[17] In line with the data, this statement assumes that the gender gaps in wage rates, earnings, and inter-firm mobility are all positive, $\Delta w > 0$, $\Delta w + \Delta h > 0$, and $\Delta\eta > 0$. $\Delta w|_{\Delta a}/\Delta w$ is larger in the full model since

Table 1: Summary of main qualitative implications.

	full model (endogenous mobility)	**reference model** (exogenous mobility)
Equilibrium gender gap in...		
... pay, Δw	$\frac{\eta+1}{\eta} \cdot \Delta a + \frac{1}{\eta} \cdot \Delta\gamma + \frac{1}{\eta} \cdot \Delta h$	$\Delta a + \frac{1}{1+\eta} \cdot \Delta\gamma$
... inter-firm mobility, $\Delta\eta$	$\frac{\eta+1}{\eta} \cdot \Delta a + \frac{\eta+1}{\eta} \cdot \Delta\gamma + \frac{\eta+1}{\eta} \cdot \Delta h$	$\Delta\gamma$
Required gender gap in...		
... labor-demand factors, Δa	$\Delta w - \frac{1}{1+\eta} \cdot \Delta\eta$	$\Delta w - \frac{1}{1+\eta} \cdot \Delta\eta$
... job-related preferences, $\Delta\gamma$	$\Delta\eta - \Delta w - \Delta h$	$\Delta\eta$
Share of wage gap explained by...		
... labor-demand differences, $\Delta w\|_{\Delta a}/\Delta w$	$\frac{\eta+1}{\eta} \cdot \frac{\Delta w - \frac{1}{1+\eta}\Delta\eta}{\Delta\eta}$	$\frac{\Delta w - \frac{1}{1+\eta}\Delta\eta}{\Delta\eta}$
... preference differences, $\Delta w\|_{\Delta\gamma}/\Delta w$	$\frac{1}{1+\eta} \cdot \frac{\Delta\eta - \Delta w - \Delta h}{\Delta w}$	$\frac{1}{1+\eta} \cdot \frac{\Delta\eta}{\Delta w}$
... labor-supply differences, $\Delta w\|_{\Delta h}/\Delta w$	$\frac{1}{\eta} \cdot \frac{\Delta h}{\Delta w}$	0
Share of mobility gap explained by...		
... labor-demand differences, $\Delta\eta\|_{\Delta a}/\Delta\eta$	$\frac{\eta+1}{\eta} \cdot \frac{\Delta w - \frac{1}{1+\eta}\Delta\eta}{\Delta\eta}$	0
... preference differences, $\Delta\eta\|_{\Delta\gamma}/\Delta\eta$	$\frac{\Delta\eta - \Delta w - \Delta h}{\Delta\eta}$	1
... labor-supply differences, $\Delta\eta\|_{\Delta h}/\Delta\eta$	$\frac{\eta+1}{\eta} \cdot \frac{\Delta h}{\Delta\eta}$	0

differently, the result implies that a model that neglects the endogeneity of inter-firm mobility overstates the importance of preference differences between genders and understates that of labor-demand factors.[18]

Additionally, the model with endogenous mobility has a role for labor-supply differences between men and women in explaining the wage gap. When women supply less labor than men, their wage rates are less important to households, setting in motion the feedback loop. Hence, a part of the gender wage gap is due to households supplying less female than male labor which in turn may reflect advantages of women in non-market activities such as child-rearing or breast-feeding or social norms regarding gender roles in the family.

$(\eta+1)/\eta > 1$. $\Delta w|_{\Delta\gamma}/\Delta w$ is smaller in the full model since $\Delta w + \Delta h > 0$. $\Delta\eta|_{\Delta a}/\Delta\eta$ is larger in the full model since it is positive there and zero in the reference model. $\Delta\eta|_{\Delta\gamma}/\Delta\eta$ is smaller in the full model since $\Delta w + \Delta h > 0$.

[18] To clarify, my full model does not yield larger gender differences in labor-demand factors such as productivity or experience. In fact, the calibration of both model versions delivers the same Δa. Rather, the full model explains a larger share of the gender gaps in pay and inter-firm mobility with this given difference due to the amplifying feedback loop between the gender gaps in pay and inter-firm mobility discussed above.

2.6 Testable prediction

Going back to Manning (2003), quit regressions are applied to measure inter-firm mobility as the responsiveness of quits to wage rates. On monopsonistic labor markets, workers leave better paying firms at lower rates and the slope of this relation is closely connected to the elasticity of labor supply to individual firms. My theory implies this slope to depend on household earner roles because quits, like any workplace choice, result from a weighing of pay and non-pay characteristics of jobs and households put more weight on pay for members contributing larger shares to earnings.

In the structure of the model, quit rates are easy to determine.[19] Some firms have slightly higher marginal revenue products of labor than others and thus pay slightly higher wages. These firms are chosen by workers slightly more often and are thus slightly larger. Specifically, a firm j that is paying ε_j more relative to other firms employs $\delta_{j,g} = \eta_g \epsilon_j$ more workers of gender g relative to other firms, its size being given by $n_{j,g} = (1/V)(1 + \delta_{j,g})$. Equilibrium quits follow from the reshuffling of worker preferences over firms each period. The total size of a firm does not change, it has equally large inflows and outflows of workers. Of the $n_{j,g}$ workers of gender g working for firm j in any given period, $\theta n_{j,g}$ workers obtain new preferences over firms going into the next period and thus potentially quit. Yet, a fraction of these workers with new preferences choose firm j as their employer also under their new preferences. Specifically, these are $\theta n_{j,g}^2$ workers. Hence, the firm is left by $Q_{j,g} = \theta n_{j,g} - \theta n_{j,g}^2$ workers and has a quit rate of $q_{j,g} = Q_{j,g}/n_{j,g} = \theta(1 - n_{j,g})$. Using the result on the firm's size from above gives

$$q_{j,g} \approx \theta \left(1 - \frac{1}{V}\left(1 + \eta_g \varepsilon_j\right)\right) \tag{13}$$

where ε_j is the firm-specific component in log wages, $\log(w_{g,j}/w_g)$, with w_g denoting the average wage rate paid to workers of group g. It up to first order equals the firm-specific

[19] Web Appendix A.4 provides additional details.

component of the marginal revenue product of wages. Economically, θ is the fraction of workers drawn to receive new job-specific preferences and $1/V \cdot (1+\eta_g)$ describes the fraction of those workers who nonetheless continue to work on their previous jobs. This fraction is higher when the firm pays higher wages and the sensitivity depends on the elasticity η_g derived before. Importantly, η depends on an individual's contributed share to household earnings, $e_i = w_i h_i / (w_i h_i + w_{-i} h_{-i})$, and, with some in-group variation in this measure, this prediction can be tested in a regression of the form

$$q_i = \beta_0 + \beta_1 \cdot \log w_i + \beta_2 \cdot (e_i - 0.5) \cdot \log w_i + \beta_3 \cdot e_i + X_i \varphi + \zeta_i, \tag{14}$$

in a random sample of workers of group g indexed by i. q_i describes a subsequent quit by worker i, w_i is the wage rate currently paid to worker i, the controls X_i account for the overall (average) pay to workers like worker i, and ζ_i is a residual.

Using (13), the expected regression coefficients are given by

$$\mathrm{E}\,\widehat{\beta}_1 = \frac{\partial q_i}{\partial \log w_i}|_{e_i=0.5} = -\frac{\theta}{V}\eta_g(e = 0.5) = -\frac{\theta\gamma}{2} < 0$$

and

$$\mathrm{E}\,\widehat{\beta}_2 = -\frac{\theta}{V}\frac{\eta}{e} = -\theta\gamma < 0, \tag{15}$$

where γ, η, and e without indices are group-specific means. While a large class of models predicts a negative relation between wages and quits, it is the main testable prediction of my theory that this link is stronger where relative contributions to household earnings are large, i.e., that regression (14) yields a negative coefficient on the interaction term, see (15).

Linking regression results to firm-level labor-supply elasticities. Equation (13) shows that the average marginal effect of the log wage on the quit probability is proportional to the firm-level labor-supply elasticity η. Hence, differences and similarities in the estimated marginal effects can be interpreted as differences and similarities in η. For quantitative interpretations of the estimates, I determine a ballpark number for the proportionality factor

θ/V. I use the most recent estimate for the Herfindahl index of Berger et al. (2022). He reports a value of 0.11 which is equivalent to around $V \approx 9$ equally sized firms. The average quit rate in the model is given by $\theta(1 - 1/V)$ and ranges empirically at around 20% per year. This can be used to solve for θ as $\theta \approx 0.2/(1 - 1/9) = 0.225$. Together, this implies that the proportionality factor is in the ballpark of $\theta/V \approx 0.225/9 = 1/40$. Put differently, average labor-supply elasticities to individual firms are around 40 times the estimated marginal effect. Such quantitative interpretations have to be taken with a considerable grain of salt, however. The monopsony literature has identified several problems that can result in biased estimates of separations elasticities, among them the importance of effectively controlling for determinants of alternative wage offers, unobserved heterogeneity, and the lack of identified exogenous wage variation at the firm level. Yet, the literature tends to view the resulting biases as rather constant, implying rather high confidence in at least qualitative interpretations (see Langella and Manning, 2021).

3 Empirical analysis

3.1 Specification and data

To implement the procedure outlined in Section 2.6, I use data from the Panel Study of Income Dynamics (PSID). Its panel structure allows me to construct quits because I can observe if a job continues to the next wave and, if it does not, who ended the job, the worker or the firm. Further, since the PSID is a household survey, it contains rich information on workers and their spouses, which is crucial for my purposes. Yet, this information comes at the price of having relatively little information about firms compared to data from a firm panel or linked employer-employee data.[20]

[20] Requiring information on the family background induces me to concentrate on the quit margin as also done by, e.g., Ransom and Oaxaca (2010), Depew and Sørensen (2013), and Hirsch et al. (2022) while some studies also consider the responses of hires from employment to wage rates in order to quantify the recruit elasticity separately from the quit elasticity (Hirsch et al. 2010; Hirsch et al. 2018). The PSID allows to construct quits but, as a household survey, has no information on firms' hiring behavior. Such information is available in linked employer-employee data like the German LIAB, used by, e.g, Hirsch, Jahn, and Schnabel (2018), but this data has no information on family background which is indispensable for my analysis.

I select a sample of roughly 40,000 jobs ijt held by married individuals between 1978 and 1996 for which I observe wage rates, region, the worker's age, education, race, number of children, and total household earnings, as well as whether the job continued to exist in the next year and, if it does not, the reason for its non-continuation. The sample ends in 1996 because the PSID turned biennial in 1997 making 1996 the last year for which I know whether jobs still existed the next year. The sample starts in 1978 because the PSID contains information on the reasons of worker-firm separations for both genders continuously from 1979 (hence jobs held in 1978) on. For full transparency, Web Appendices B.1, B.2, and B.3 provide detailed descriptions of the definition of variables, the sample selection, and the specification of the different regressions.

As my baseline regression, I estimate

$$q_{ijt} = \beta_0 + \beta_1 \cdot \log w_{ijt} + \beta_2 \cdot (e_{it} - 0.5) \cdot \log w_{ijt} + \beta_3 \cdot e_{it} + X_{it}\varphi_1 + Y_{it}\varphi_2 + \zeta_{ijt},$$

where i indexes the individual, j the firm, and t time. I measure the earnings contribution as its deviation from earnings parity, 0.5. This choice does not affect the coefficient on the interaction term, β_2, but allows to interpret the coefficient on the non-interacted log wage rate, β_1, as the wage sensitivity of quits at earnings parity in the household. In order to estimate the coefficient on the interaction term consistently, I include the (non-interacted) earnings share and linear-quadratic interaction between the log wage rate and time, summarized in Y_{it}. The latter interaction is necessary because spouses' contributed shares to household earnings have gender-specific trends reflecting the closure of the gender gap in earnings such that the interaction $\log w_{ijt} \cdot e_{it}$ could pick up trends in the wage sensitivity of quits rather than the influence of relative earnings within the worker's household.[21] The vector X_{it} collects determinants of the worker's alternative wage offers from other firms which are unobservable in the data. Following Manning (2003), I include in X dummies for

[21] In a robustness check, I exclude the interaction with time which has only small effects on results.

year, education, the number of children, region, and race.[22]

The monopsony literature mostly has to rely on observational wages as it aims to analyze the effects of pay differences between an existing match and a potential alternative match for the worker. This rules out the use to worker characteristics such as industry or age or aggregate variables such as tax rates as wage instruments because they also impact on the worker's (net) pay at other employers. Few papers (e.g., Staiger et al., 2010) have used quasi-experimental firm-specific wage variations which can circumvent this problem. Such an approach is impossible in my data where the respondent's employer is unknown. Yet, crucially, it is known whether the respondent's employer is the same as in the year before.

I also run specifications instrumenting the earnings contribution e_{it} and account for the potential role of parenthood. In robustness checks, I estimate non-linear models, interact the control variables with the earnings contribution, vary the set of control variables, include fixed effects, account for potential non-linear effects of the wage rate, and separately consider the impact of the different variables that enter the construction of the earnings contribution.

3.2 Results

Table 2 summarizes the main results. The table shows the coefficients on the log wage rate and on the interaction term in the baseline specification, separately for men and women. The numbers in brackets are standard errors and asterisks indicate statistically significant difference from zero (at 10%, 5%, and 1%, respectively).

First, I consider a specification where I omit the interaction term between wages and the contributed earnings share, see columns (1) and (2) of Table 2. In line with the literature, I find quite substantial gender differences in the estimates. The quit behavior of women is, on average, substantially less wage-sensitive than that of men. Quantitatively, the coefficient for women is about a third smaller than that for men, similar to the results of Ransom and

[22] Following the literature, I estimate regressions separately for men and women because alternative wage offers cannot be expected to depend on the included control variables in the same way for men and women.

Table 2: Results of baseline quit regressions, PSID data.

	(1) men	(2) women	(3) men	(4) women
log wage rate	-0.0488^{***}	-0.0294^{**}	-0.0465^{***}	-0.0469^{***}
	(0.0158)	(0.0164)	(0.0158)	(0.0171)
log wage rate			-0.0389^{***}	-0.0579^{***}
$\times$ (earnings share-0.5)			(0.0130)	(0.0162)
observations	20231	20131	20231	20131
marginal effect of $\log w$...				
... at mean earnings shares			-0.0531^{***}	-0.0375^{**}
($e_m = 0.67, e_f = 0.33$)			(0.158)	(0.165)
... at earnings parity			-0.0465^{***}	-0.0469^{***}
($e_m = e_f = 0.5$)			(0.0158)	(0.0171)

Notes: Dependent variable: quit between observation year and following year; linear probability models; standard errors in parentheses; *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$; alternative wage determinants (X, dummies): year, education, region, race, kids; additionally included variables: constant, earnings share, $\log w \times t$, $\log w \times t^2$. Variable definitions, sample selection, and specification described in detail in Web Appendices B.1, B.2, and B.3, respectively.

Oaxaca (2010) and Hirsch et al. (2010).

Columns (3) and (4) report results for my baseline specification including the interaction term. The results support strongly the model prediction that inter-firm mobility depends on earner roles within the household. For both men and women, the coefficient on the interaction term is significantly negative which shows that a higher share in household earnings raises the sensitivity of quits to wages as predicted by my model.

Note that the coefficient on the (non-interacted) log wage rate is now very similar between genders. Put differently, once different earner roles are accounted for, only small gender differences in inter-firm mobility remain. Through the lens of my model, this indicates that gender differences in the direct importance of non-pay job attributes are small. Put differently, my estimation results indicate that women are on average less mobile between firms primarily because of their earner roles within the household.

For illustration, the bottom part of the table gives the marginal effect of the log wage rate at two relevant points in the distribution of contributed earnings shares. Similarly,

Figure 2: Estimated wage sensitivity of quits as a function of the husband's contributed share to household earnings (marginal effect).

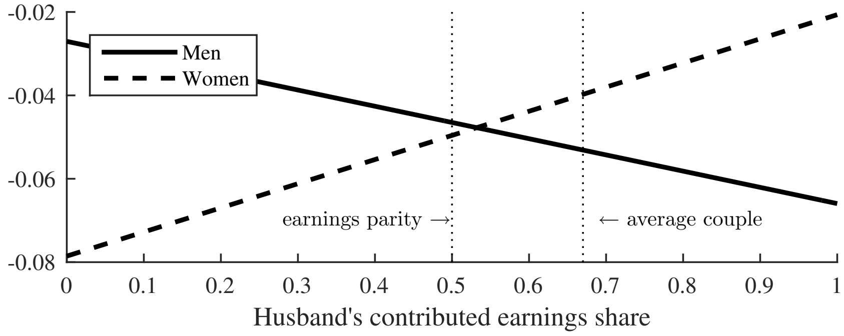


Figure 2 plots the marginal effect of the log wage rate on the quit probability as a function of the *husband's* earnings contribution (hence, for wives, one minus their own contribution). Both exhibits illustrate that mobility differences between genders reflect household earner roles. At their respective average earnings contributions, women's quit behavior is substantially less sensitive to wages than men's. By contrast, the empirical model predicts that, if husbands and wives contributed equal shares to household earnings ("earnings parity"), they would also show a similar mobility between firms.

Robustness. Table 3 contains results of additional estimations that assess sensitivity regarding various aspects of the empirical strategy. The main results are confirmed, but significance is weaker in some specifications. I first account for the fact that household earner roles depend on how much a person could earn, including how strongly this person is discriminated against by monopsonistic firms. Earner roles may endogenously react to mobility between firms and quit probabilities. I use an IV strategy to address this point. Specifically, I instrument an individual's earnings share by the Mincer variables of the individual and the individual's partners. In the framework of a quit regression, the individual's Mincer variables have to be included in the second stage to account for alternative wage offers, but the partner's Mincer variables serve as *excluded* instruments for e_{it}. While partners' Mincer variables are correlated due to assortative mating (e.g., Bredemeier and Jüßen, 2013), the residual earnings potential of the partner is an exogenous source of an individual's earnings share within the household. As additional information on the partner's earnings potential, I include the partner's industry and occupation. When I follow this strategy, I find my main results confirmed, see first row in Table 3. Coefficients on the interaction term are significantly negative. Not surprisingly, standard errors are larger as, here, they also include first-stage uncertainty.

Next, I want to rule out that my results are driven by the presence of children in a household. The birth of a child could be an event that leads to a reduction in the mother's earnings through reduced hours worked (and hence a reduction in her contributed share to household earnings) and simultaneously to an increased importance of non-pay characteristics of the mother's job (such as distance to a child-care facility), without the causality running through her earnings share. I address this point in two specifications. First, I restrict the sample to parents with children living in the household. Here, results cannot be driven by differences in earnings shares and importance of non-pay job characteristics between parents and non-parents. In this specification, I still find significantly negative coefficients on the interaction terms, see second row of Table 3. Second, I additionally include an interaction between the number of children and the log wage rate that should pick up the effect of children on the wage sensitivity of job choices independent of relative earnings. Put differently, the coefficient on the interaction of the wage rate and the earnings share measures the effect of earnings on inter-firm mobility conditional on a given number of children. I find my main results confirmed, see third row of Table 3.[23]

My baseline regressions include quits into out of labor force but such quits do not occur in my model. Therefore, I also estimate the quit regressions for a sample of individuals who remain in the labor force in the subsequent year ($t+1$). The coefficients on the interaction of the wage and the earnings share remain negative, see fourth row of Table 3, showing that

[23] As one would expect, the coefficient on the interaction between children and the log wage rate is negative for men and positive for women. Hence, children tend to make workplace choices more wage-sensitive for fathers and less wage-sensitive for mothers. However, this effect of children is not driving my main results. I also estimated my baseline specification for married couples without children in the household and also find negative coefficients on the interactions of wage rates and earnings shares but estimates are less precise in this relatively small sample consisting mostly of relatively young or relatively old workers.

Table 3: Coefficient on interaction between earnings share and wage rate in quit regressions when accounting for the potential endogeneity of the earnings contribution, the role of children, and transitions out of labor force, respectively.

		men	**women**
i.	earnings share instrumented	-0.0457^{*}	-0.0951^{**}
		(0.0320)	(0.0443)
ii.	parents only	-0.0279^{*}	-0.0668^{***}
		(0.0160)	(0.0188)
iii.	include interaction with no. of children	-0.0376^{***}	-0.0558^{***}
		(0.0004)	(0.0165)
iv.	remain in labor force	-0.0338^{**}	-0.0396^{*}
		(0.0172)	(0.0219)

Notes: Results from quit regressions; coefficients on the interaction term between log wage rate and the earnings share; standard errors in parentheses; *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$; alternative wage determinants (X, dummies): year, education, region, race, kids; additionally included variables: constant, e, $t \times \log w$, Xe. Variable definitions, sample selection, and specification described in detail in Web Appendices B.1, B.2, and B.3, respectively.

my results indeed reflect the quitting behavior of workers transitioning to a new job.

To check sensitivity with respect to the econometric specification, I consider a number of respecifications of my baseline regression, see Table 4. The first and second lines in Table 4 show the marginal effects of the interaction term in probit and logit models, respectively. Also here, the coefficient on the interaction term is significantly negative for both men and women. The third line allows for non-linear effects of the wage rate as in Depew and Sørensen (2013) by including a cubic of the wage rate. This is an interesting extension since the documented effect of the earnings contribution may reflect a non-linear effect of the wage rate. The results show that it does not, because the coefficients on the interaction terms are still significantly negative when controlling for higher orders of the wage rate. The fourth line reports results for a specification where I omit the interaction between the log wage rate and time, which also does not impact on the main results. The fifth line of Table 4 takes into account that workers with higher contributions to household earnings should also react more strongly to alternative wage offers by interacting the alternative wage

Table 4: Robustness checks.

		men	**women**
i.	probit	-0.0515^{***}	-0.0544^{***}
		(0.0135)	(0.0148)
ii.	logit	-0.0544^{***}	-0.0870^{***}
		(0.0135)	(0.0169)
iii.	polynomial in $\log w$	-0.0385^{**}	-0.0833^{***}
		(0.0189)	(0.0190)
iv.	no time interaction	-0.0449^{***}	-0.0519^{***}
		(0.125)	(0.158)
v.	interact controls	-0.0383^{***}	-0.0500^{***}
		(0.0134)	(0.0162)
vi.	include tenure	-0.0356^{***}	-0.0295^{*}
		(0.0128)	(0.0160)
vii.	fixed effects	-0.0372^{**}	-0.0442^{*}
		(0.0182)	(0.0230)

Notes: Results from quit regressions; coefficients on the interaction term between log wage rate and the earnings share; average marginal effects for probit and logit; standard errors in parentheses; *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$; alternative wage determinants (X, dummies): year, education, region, race, kids; additionally included variables: constant, e, $t \times \log w$, Xe. Variable definitions, sample selection, and specification described in detail in Web Appendices B.1, B.2, and B.3, respectively.

determinants X with the earnings contribution. Also here, the coefficients on the interaction term remain negative. The sixth line includes tenure as a control variable as discussed by Manning (2003). While this impacts on the precision of the estimate for women, it does not affect substantially the point estimates. As a final check, the seventh line includes individual fixed effects to make sure that every (time-invariant) determinant of alternative wage offers is accounted for.[24] Most households remain in my sample for six to seven years and switching jobs is relatively rare such that including fixed effects comes at the cost that the identification is no longer derived through *which* jobs are quit but through *when* they are quit. For this reason, the baseline regressions do not include fixed effects. The results in

[24]I omit age in this specification due to its linearity in time at the within-individual perspective.

Table 5: Interaction with alternative variables

		men	**women**
i.	own earnings	-0.0044^{**}	-0.0094^{***}
		(0.0017)	(0.0018)
ii.	own wage rate	-0.0047^{***}	-0.0045^{**}
		(0.0017)	(0.0021)
iii.	own hours	-0.0031	-0.0108^{***}
		(0.0072)	(0.0028)
iv.	partner's earnings	0.0048^{*}	0.0083^{*}
		(0.0024)	(0.0050)
v.	average household earnings	0.0421^{**}	0.1587^{***}
		(0.0178)	(0.0227)

Notes: Results from quit regressions; coefficients on the interaction term between log wage rate and the indicated variable; p-values in parentheses; *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$; alternative wage determinants (X, dummies): year, education, region, race, kids; additionally included variables: constant, the indicated variable, $t \times \log w$. Variable definitions, sample selection, and specification described in detail in Web Appendices B.1, B.2, and B.3, respectively.

the seventh line of Table 4 reveal that this specification choice is relatively innocuous: I find significantly negative coefficients on the interaction terms also in a fixed-effects regression.

Since an individual's contributed share to household earnings is a constructed variable, I also perform estimations where I interact the log wage rate with the share's components. Table 5 reports the results. In line with the model, workers are found to supply labor more elastically to individual firms (hence, their wage sensitivity of quits, which is negative, is smaller) if they earn more, have higher wage rates, work longer hours, or are married to partners with lower earnings.[25] This corroborates the finding that my main results reflect more than a simple non-linear effect of the wage rate itself. The final line addresses the possibility of intertemporal consumption smoothing. In presence of substantial fluctuations in household earnings, marginal utility of consumption would be determined by average rather than current household earnings if the household has access to sufficient consumption-

[25] It is not surprising that the effect of the interaction with hours worked is estimated imprecisely for men due to the low variation of hours worked among men.

smoothing possibilities. The results confirm the model prediction that households with higher average earnings supply labor of their members less elastically (the coefficient is positive thereby dampening the negative effect of wage rates on quit probabilities).

4 Quantitative analysis

4.1 Extended model

I now quantify my theoretical results regarding the feedback loop between gender gaps in pay and inter-firm mobility. To this end, I extend my model to take into account further aspects of employer choices, labor-market competition, and the gender wage gap. The main extensions are an endogenous hours choice, the inclusion of singles, within-gender heterogeneity, and considering more dimensions of labor supply, i.e., allowing for vertical (e.g., industry or occupation) and horizontal (e.g., education or career) choices of workers.

For brevity, I only provide a high-level overview of the quantitative model and delegate the detailed description of all modeling choices and the calibration to Web Appendix C. There, I also consider additional model versions aimed at addressing further aspects such as home production, gender differences in the elasticity of labor supply to the market, firm entry, and the type of wage competition between firms.

Additional model features. Segregation of men and women into different segments of the labor market is an important force behind the gender wage gap (see, e.g., Blau and Kahn, 2017). I incorporate the possibility of vertical and horizontal segregation by allowing workers to choose from horizontal industry-occupation cells that differ in the degree of labor-market competition between firms and from vertical segments of the labor market that differ in a worker's marginal revenue product (as a short-cut for education). Individuals have preferences over the different segments of the labor market like they have preferences over workplaces within these segments. Further, I allow for within-gender (and within-education) heterogeneity in productivity which affects a worker's marginal revenue product in a firm.

While hours worked are exogenous in the basic model, the quantitative model features an endogenous choice of labor supply at the intensive margin. I do so because hours worked are an additional margin at which households can react to pay differences between men and women and a factor that determines the importance of hourly pay for workplace choices. Gender differences in the weight on the disutility from work measure differences in households' willingness to supply the labor of men and women. They may reflect the bargaining power of the spouses, their preferences, their productivity in non-market work, and also on social norms regarding gender roles.

Finally, my proposed mechanism is absent for singles and ignoring singles may hence lead to an overestimation of the mechanism's importance. In the quantitative model, I therefore incorporate singles who are just like married individuals except for having no partner.

Calibration. The model is calibrated to the contemporary U.S. economy. First, I set the share of couple households, the Frisch elasticity of market labor supply, the time preference rate, and the process for firm productivity shocks, to empirical averages or estimates from the literature. Importantly, gender-specific productivity distributions and utility weights on labor supply and job attributes are disciplined by the observed gender gaps in wages rates, hours, and estimated firm-level labor-supply elasticities. The share of workers with re-drawn job preferences is set targeting the overall quit rate. Productivity shifters responsible for vertical segregation are quantified targeting the college wage premium, while taste shifters inducing horizontal segmentation are calibrated to observed differences in industry concentration. Overall, the parametrization ensures that both aggregate labor-market features and gender-specific outcome gaps are matched closely to U.S. data.

A key property of the resulting calibration is that the model does not need large exogenous differences between genders. Specifically, the gender gap in average productivity is only about 13 log points while the gender gap in wage rates, which amplifies the productivity gap through monopsonistic discrimination and gender segregation, is about 20 log points. Most importantly, I need to put into the model only very small gender differences in the importance of non-pay job characteristics. The gender gap in the exogenous utility parameter γ is only about 6% while men are roughly a third more mobile between firms than women. Put differently, only about one fifth of the gender gap in inter-firm mobility the model devotes to exogenous factors while over 80% of the gap are explained endogenously.

The model reproduces several empirical patterns without targeting them directly. It generates marriage premia for men and marriage penalties for women, consistent with observed differences between singles and couples, as well as realistic part-time penalties arising from reduced inter-firm mobility of secondary earners. Beyond wage outcomes, the model successfully replicates the empirical relationship between quits and wages: simulated quit regressions closely resemble their real-world counterparts and confirm that household earner roles, rather than intrinsic gender preferences, drive observed differences in inter-firm mobility. See Web Appendix C for details. These results provide confidence that the framework captures key mechanisms of the labor market and is well-suited for counterfactual analysis.

4.2 Counterfactual analysis

I perform two series of counterfactuals. The first is a decomposition of observed gender gaps in wage rates, earnings, and mobility into the effects of the three main driving forces, i.e., exogenous differences in labor demand, labor supply, and the importance of non-pay job characteristics. The second analyzes the amplification of changes in these exogenous factors through the feedback loop.

Decomposition. To decompose gender gaps in labor-market outcomes, I perform counterfactual model evaluations where I shut off exogenous gender differences by setting the respective parameter for women to its value for men. Specifically, I first shut off gender differences in the utility weight on hours. Second, I shut off gender differences in the utility weights on non-pay job attributes. Third, I shut off both these gender differences in pref-

Table 6: Endogenous gender gaps (in log points) in baseline calibration and in counterfactuals shutting off exogenous gender gaps in preferences.

	full model (endogenous mobility)			**reference model** (exogenous mobility)		
	wage gap	earnings gap	mobility gap	wage gap	earnings gap	mobility gap
A) full calibration	19.9	32.6	29.7	19.9	32.6	29.7
B) hours weight gap shut off	18.6	26.3	25.7	19.5	26.9	29.7
C) non-pay weight gap shut off	17.8	29.9	22.1	12.6	22.9	0.0
D) both preference gaps shut off	16.6	23.6	17.2	12.3	17.2	0.0
Relative contribution (%) of ...						
... labor-demand gap ($= D/A$)	83.8	72.4	57.9	62.1	52.8	0
... non-pay weight gap ($= (B-D)/A$)	10.1	8.3	28.6	36.4	29.8	100
... labor-supply gap ($= (C-D)/A$)	6.1	19.3	13.1	1.5	17.5	0

Notes: Levels of wage rates, hours, and elasticities of labor supply to individual firms shown in Table 13 in Web Appendix C.5.

erences. I do this for my full model and for a reference model in which I treat inter-firm mobility as exogenous, i.e., where η is a parameter.

The results are shown in the upper block of Table 6 where the left part refers to my full model and the right part refers to the reference model with exogenous mobility. The numbers in the table give the gender gaps in wage rates, earnings, and inter-firm mobility in the different counterfactuals (in log points). The lower block of the Table 6 shows the percentage contributions of the different exogenous gender gaps on the endogenous gaps, as implied by the counterfactual evaluations.

My full model generates substantial gender gaps in wage rates, earnings, and inter-firm mobility also without gender differences in preferences. Without any gender differences in preferences (row D), i.e., with gender differences only in labor-demand factors, the model still generates almost five-sixths of the gender wage gap, almost three-quarters of the gender gap in earnings, and almost three-fifths of the gender gap in inter-firm mobility. The reference model with exogenous inter-firm mobility assigns substantially less importance to gender differences in labor-demand factors.

Reversely, the contribution of gender gaps in preferences to gaps in outcomes is limited in my full model. In particular, the gender gap in the importance of non-pay job characteristics contributes only 10% to the gender wage gap and, strikingly, only less than 30% to the gender gap in inter-firm mobility.[26] In the reference model with exogenous inter-firm mobility, by contrast, gender differences in the importance of non-pay job characteristics explain more than 35% of the gender wage gap and, by construction, 100% of the gender gap in inter-firm mobility. Put differently, a model without endogenous inter-firm mobility strongly overestimates the causal role of gender differences in preferences over jobs.

As discussed in Section 2, my model suggests that gender differences in labor-supply factors influence how mobile men and women are between firms and how strongly firms can discriminate monopsonistically against women. The quantitative results in Table 6 show that this effect is modest, but not negligible, as about 6% of the gender wage gap is assigned to gender differences in labor-supply factors. In the reference model, labor-supply factors only exert a small effect on gender-specific wages through composition effects.

Amplification. I now vary parameters in order to assess the quantitative degree of amplification due to endogenous inter-firm mobility. Specifically, in each experiment, I close one of the gender gaps in exogenous parameters by making women more similar to men in the respective dimension. The numbers in Table 7 give the absolute change (in log points) in the gender gaps in wage rates, earnings, and inter-firm mobility induced by a ten log point reduction in one of the three exogenous gender gaps. As in Table 6, the left block shows the results for my full model with endogenous inter-firm mobility while the right block shows the results for the reference model where inter-firm mobility is exogenous.

First, I raise firms' demand for female labor by raising women's average productivity by ten log points. In the reference model with exogenous inter-firm mobility, this closes the gender wage gap by little more than ten log points and, by construction, leaves the gender gap in inter-firm mobility untouched. By contrast, in my full model, effects are amplified

[26] The latter number is larger than the 20% which results from a direct comparison of $\Delta\gamma$ and $\Delta\eta$ because the (small) $\Delta\gamma$ generates some endogenous earnings gap and thus also exerts an indirect, general-equilibrium effect on $\Delta\eta$ in my full model.

Table 7: Changes in endogenous gender gaps (in log points) induced by closing exogenous gender gaps by ten log points.

	full model (endogenous mobility)			**reference model** (exogenous mobility)		
	wage gap	earnings gap	mobility gap	wage gap	earnings gap	mobility gap
Closure of gap in...						
...labor demand	-13.9	-19.1	-12.1	-10.8	-14.5	0
...labor supply	-1.3	-6.4	-4.0	-0.2	-4.8	0
...weight on non-pay	-3.2	-4.4	-13.9	-2.5	-3.4	-10.0

Notes: Closures of exogenous gaps achieved through changing female parameter accordingly. Levels of wage rates, hours, and elasticities of labor supply to individual firms shown in Table 13 in Web Appendix C.5.

through the feedback loop between gender gaps in pay and inter-firm mobility. The effect on the gender wage gap is amplified by about 30% as the gap closes by about 14 log points in my full model. The reduction in the gender gap in inter-firm mobility is also considerable which reduces firms' ability to discriminate monopsonistically against women.

Second, I reduce the gender gap in the exogenous utility weight on labor supply inducing households to increase female labor supply. In the model with exogenous mobility, this has only a very small effect on the gender wage gap stemming from more women choosing better paying labor-market segments. Again, the gender gap in inter-firm mobility is unaffected by construction. Also here, effects are substantially stronger in my full model with endogenous inter-firm mobility. The reduction in the gender wage gap is more than six times as strong due to the endogenous increase in women's relative inter-firm mobility raising their pay.

Third, I reduce women's exogenous preference weight on non-pay job attributes which makes them more mobile between firms. In my model, this exogenous impulse is amplified through the feedback loop and the gender gap in inter-firm mobility is reduced by about 14 log points. This also leads to a quite substantial reduction in the gender wage gap by more than 3 log points. Effects are substantially smaller in the reference model.

The counterfactual changes in the exogenous gender gaps can be used to think about the effects of policy in my model. A narrowing of the gap in labor demand can be understood as a stand-in for anything that induces a movement along the relative labor-supply curve of men versus women. Examples could be payroll subsidies that differ by gender of the worker or an elimination of the high marginal tax rates imposed on secondary earners under progressive joint taxation. Similarly, a change in relative labor supply can be thought of as anything that lets households change the proportion at which they supply male and female labor for given relative wage rates. Policy examples that may raise female labor supply could be, for example, extended access to child care and reforms of divorce or alimony legislation. Finally, there can be policies that effectively change the utility weight on non-pay job characteristics through making firms more similar in certain dimensions of non-pay job attributes. For example, if allowing child-sick leave is mandatory for firms, this is one less dimension in which firms differ and this may make especially women more mobile between firms. In my model, the effects of such policies are amplified by reinforcing changes in relative wage markdowns imposed on men and women by monopsonistic firms. Put differently, my analysis suggests that such policies have substantially stronger effects on gender gaps in labor-market outcomes than one would expect if one neglected the endogeneity of inter-firm mobility.

5 Conclusion

In this paper, I argue that the gender gap in inter-firm mobility is largely due to men's and women's different earner roles within households, rather than intrinsic differences between genders. This relation stems from a structural model where households decide endogenously how important pay and non-pay characteristics are for the job choices of their members. I have presented direct empirical evidence on the role of relative earnings within households for the quitting behavior of workers that supports my theoretical prediction. Quantitative model evaluations suggest that the endogeneity of inter-firm mobility is important. If one mistakes inter-firm mobility as exogenous, one underestimates the role of labor-demand and labor-supply factors for the gender wage gap, overestimates the role of gender differences in the importance of different job attributes, and underestimates the effects of gender-targeted policy reforms and changes in social norms.

In future research, it would be interesting to analyze the implications of endogenous and thus heterogenous worker mobility for the relative efficiency effects of minimum wages and wage subsidies on monopsonistic labor markets. It would also be worthwhile to examine the extent to which equal pay legislation might fall flat if the underlying characteristic along which monopsonistic employers discriminate is not gender but a worker's role in the household. Finally, studying the interaction between spouses' job choices, pay differences between spouses, and the marriage market or testing my theory using data from same-sex couples also constitute promising avenues for future research.

References

Alesina, A., A. Ichino, and L. Karabarbounis (2011). Gender-based taxation and the division of family chores. *American Economic Journal: Economic Policy 3*, 1–40.

Artz, B., A. H. Goodall, and A. J. Oswald (2018). Do women ask? *Industrial Relations 57*(4), 611–636.

Autor, D., A. Kostøol, M. Mogstad, and B. Setzler (2019). Disability benefits, consumption insurance, and household labor supply. *American Economic Review 109*(7), 2613–54.

Averkamp, D., C. Bredemeier, and F. Juessen (2024). Decomposing gender wage gaps - A family economics perspective. *The Scandinavian Journal of Economics 126*(1), 3–37.

Azmat, G., C. Calsamiglia, and N. Iriberri (2016). Gender differences in response to big stakes. *Journal of the European Economic Association 14*(6), 1372–1400.

Babcock, L. and S. Laschever (2009). *Women don't ask: Negotiation and the gender divide.* Princeton University Press.

Babcock, L., M. P. Recalde, L. Vesterlund, and L. Weingart (2017). Gender differences in accepting and receiving requests for tasks with low promotability. *American Economic Review 107*(3), 714–747.

Bachmann, R. and C. Bayer (2009). Firm-specific productivity risk over the business cycle: Facts and aggregate implications. CESifo Working Paper Series 2844.

Bachmann, R. and C. Bayer (2014). Investment dispersion and the business cycle. *American Economic Review 104*(4), 1392–1416.

Bachmann, R., R. J. Caballero, and E. M. R. A. Engel (2013). Aggregate implications of lumpy investment: New evidence and a DSGE model. *American Economic Journal: Macroeconomics 5*(4), 29–67.

Barth, E. and H. Dale-Olsen (2009). Monopsonistic discrimination, worker turnover, and the gender wage gap. *Labour Economics 16*(5), 589–597.

Bayard, K., J. Hellerstein, D. Neumark, and K. Troske (2003). New evidence on sex segregation and sex differences in wages from matched employee-employer data. *Journal of Labor Economics 21*(4), 887–922.

Berger, D., K. Herkenhoff, and S. Mongey (2022). Labor market power. *American Economic Review 112*(4), 1147–93.

Bertrand, M., S. E. Black, S. Jensen, and A. Lleras-Muney (2019). Breaking the Glass Ceiling? The Effect of Board Quotas on Female Labour Market Outcomes in Norway. *Review of Economic Studies 86*(1), 191–239.

Bhashkar, V. and T. To (2003). Oligopsony and the distribution of wages. *European Economic Review 47*(2), 371–399.

Biasi, B. and H. Sarsons (2021). Flexible Wages, Bargaining, and the Gender Gap. *The Quarterly Journal of Economics 137*(1), 215–266.

Bick, A. (2016). The quantitative role of child care for female labor force participation and fertility. *Journal of the European Economic Association 14*(3), 639–668.

Bick, A. and N. Fuchs-Schündeln (2017). Quantifying the disincentive effects of joint taxation on married women's labor supply. *American Economic Review 107*(5), 100–104.

Bick, A. and N. Fuchs-Schündeln (2018). Taxation and labour supply of married couples across countries: A macroeconomic analysis. *Review of Economic Studies 85*(3), 1543–1576.

Binder, A. J., A. Eng, K. Houghton, and A. Foote (2024). Is the gender pay gap largest at the top? *AEA Papers and Proceedings 114*, 248–53.

Blau, F. D. and L. M. Kahn (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature 55*(3), 789–865.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). Consumption inequality and family labor supply. *American Economic Review 106*(2), 387–435.

Booth, A. L., M. Francesconi, and J. Frank (2003). A sticky floors model of promotion, pay, and gender. *European Economic Review 47*(2), 295–322.

Booth, A. L. and P. Katic (2011). Estimating the wage elasticity of labour supply to a firm: What evidence is there for monopsony? *Economic Record 87*(278), 359–369.

Bordalo, P., K. Coffman, N. Gennaioli, and A. Shleifer (2019). Beliefs about gender. *American Economic Review 109*(3), 739–73.

Bosquet, C., P.-P. Combes, and C. García-Peñalosa (2019). Gender and promotions: Evidence from academic economists in France. *Scandinavian Journal of Economics 131*, 1020–1053.

Braun, C., C. Nusbaum, and P. Rupert (2021). Labor market dynamics and the migration behavior of married couples. *Review of Economic Dynamics 42*, 239–263.

Bredemeier, C., J. Gravert, and F. Juessen (2019). Estimating labor supply elasticities with joint borrowing constraints of couples. *Journal of Labor Economics 37*(4), 1215–1265.

Bredemeier, C., B. Jansen, and R. Winkler (2025). Labor market power and the effects of fiscal policy. Discussion paper, University of Jena.

Bredemeier, C. and F. Jüßen (2013). Assortative mating and female labor supply. *Journal of Labor Economics 31*(3), 603 – 631.

Bredemeier, C., P. Ndlovu, S. Vujić, and R. Winkler (2025). Household decisions and the gender gap in job satisfaction. *Scotthish Journal of Political Economy 72*(1), e12403.

Bursztyn, L., T. Fujiwara, and A. Pallais (2017). 'Acting wife': Marriage market incentives and labor market investments. *American Economic Review 107*(11).

Card, D., A. R. Cardoso, J. Heining, and P. Kline (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics 36*(S1), 13–70.

Cheng, S. (2016). The accumulation of (dis)advantage: The intersection of gender and race in the long-term wage effect of marriage. *American Sociological Review 81*(1), 29–56.

Cherchye, L., B. De Rock, and F. Vermeulen (2012). Married with children: A collective labor supply model with detailed time use and intrahousehold expenditure information. *American Economic Review 102*(7), 3377–3405.

Choi, S. and A. Valladares-Esteban (2020). On households and unemployment insurance. *Quantitative Economics 11*(1), 437–469.

Croson, R. and U. Gneezy (2009). Gender differences in preferences. *Journal of Economic Literature 47*(2), 448–474.

Cullen, Z. and R. Perez-Truglia (2023). The old boys' club: Schmoozing and the gender gap. *American Economic Review 113*(7), 1703–40.

Depew, B. and T. A. Sørensen (2013). The elasticity of labor supply to the firm over the business cycle. *Labour Economics 24*(C), 196–204.

Detilleux, C. and N. Deschacht (2024). The gender gap in the wage sensitivity of job transitions: A decomposition analysis. *Journal of Labor Market Research 58*, Article 26.

Doepke, M. and M. Tertilt (2016). Families in macroeconomics. In J. B. Taylor and H. Uhlig (Eds.), *Handbook of Macroeconomics*, Volume 2 of *Handbook of Macroeconomics*, pp. 1789–1891. Elsevier.

Domeij, D. and M. Flodén (2006). The labor-supply elasticity and borrowing constraints: Why estimates are biased. *Review of Economic Dynamics 9*, 242–262.

Donni, O. and N. Moreau (2007). Collective labor supply: A single-equation model and some evidence from french data. *Journal of Human Resources 42*(1), 214–246.

Dube, A., J. Jacobs, S. Naidu, and S. Suri (2020). Monopsony in online labor markets. *American Economic Review: Insights 2*(1), 33–46.

Exley, C. L. and J. B. Kessler (2022). The gender gap in self-promotion. *The Quarterly Journal of Economics 137*(3), 1345–1381.

Félix, S. and P. Portugal (2017). Labor market imperfections and the firm's wage setting policy. Working Papers w201704, Banco de Portugal, Economics and Research Department.

Flabbi, L. and J. Mabli (2018). Household search or individual search: Does it matter? *Journal of Labor Economics 36*(1), 1–46.

Flory, J. A., A. Leibbrandt, and J. A. List (2014). Do competitive workplaces deter female workers? a large-scale natural field experiment on job entry decisions. *Review of Economic Studies 82*(1), 122–155.

Gelblum, M. (2020). Preferences for job tasks and gender gaps in the labor market. Job market paper, Harvard university.

Gobillon, L., D. Meurs, and S. Roux (2015). Estimating gender differences in access to jobs. *Journal of Labor Economics 33*(2), 317–363.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review 104*(4), 1091–1119.

Goldin, C. and L. F. Katz (2016). A most egalitarian profession: Pharmacy and the evolution of a family friendly occupation. *Journal of Labor Economics 34*(3), 705–745.

Goldin, C., S. P. Kerr, C. Olivetti, and E. Barth (2017). The expanding gender earnings gap: Evidence from the LEHD-2000 census. *American Economic Review 107*(5), 110–114.

Gomes, P. M. and Z. Kuehn (2025). You're the one that I want! Public employment and women's labor market outcomes. *American Economic Journal: Macroeconomics forthcoming*.

Groneck, M. and J. Wallenius (2020). It Sucks to Be Single! Marital Status and Redistribution of Social Security. *Economic Journal 131*(633), 327–371.

Grove, W. A., A. Hussey, and M. Jetter (2011). The gender pay gap beyond human capital: Heterogeneity in noncognitive skills and in labor market tastes. *Journal of Human Resources 46*(4), 827–874.

Grund, C. (2015). Gender pay gaps among highly educated professionals - compensation components do matter. *Labour Economics 34*(C), 118–126.

Guler, B., F. Guvenen, and G. L. Violante (2012). Joint-search theory: New opportunities and new frictions. *Journal of Monetary Economics 59*(4), 352–369.

Guner, N., R. Kaygusuz, and G. Ventura (2012a). Taxation and household labour supply. *Review of Economic Studies 79*(3), 1113–1149.

Guner, N., R. Kaygusuz, and G. Ventura (2012b). Taxing women: A macroeconomic analysis. *Journal of Monetary Economics 59*(1), 111–128.

Heinz, M., H.-T. Normann, and H. A. Rau (2016). How competitiveness may cause a gender wage gap: Experimental evidence. *European Economic Review 90*, 336 – 349.

Hernandez-Arenaz, I. and N. Iriberri (2018). Women ask for less (only from men): Evidence from bargaining in the field. *Journal of Economic Behavior & Organization 152*(C), 192–214.

Hirsch, B. (2016). Gender wage discrimination - does the extent of competition in labor markets explain why female workers are paid less than men? *IZA World of Labor 310*, 1–10.

Hirsch, B., E. J. Jahn, A. Manning, and M. Oberfichtner (2022). The urban wage premium in imperfect labour markets. *Journal of Human Resources 57*(S), S111–S136.

Hirsch, B., E. J. Jahn, and C. Schnabel (2018). Do employers have more monopsony power in slack labor markets? *Industrial and Labor Relations Review 71*(3), 676–704.

Hirsch, B., T. Schank, and C. Schnabel (2010). Differences in labor supply to monopsonistic firms and the gender pay gap: An empirical analysis using linked employer-employee data from Germany. *Journal of Labor Economics 28*(2), 291–330.

Iriberri, N. and P. Rey Biel (2021). Brave boys and play-it-safe girls: Gender differences in willingness to guess in a large scale natural field experiment. Technical report.

Keane, M. P. (2011). Labor supply and taxes: A survey. *Journal of Economic Literature 49*(4), 961–1075.

Killewald, A. and I. Lundberg (2017). New evidence against a causal marriage wage premium. *Demography 54*(3), 1007–1028.

Kuhn, P. and M. C. Villeval (2015). Are women more attracted to co-operation than men? *Economic Journal 125*(582), 115–140.

Lamadon, T., M. Mogstad, and B. Setzler (2022). Imperfect competition, compensating differentials, and rent sharing in the us labor market. *American Economic Review 112*(1), 169–212.

Langella, M. and A. Manning (2021). Marshall lecture 2020: The measure of monopsony. *Journal of the European Economic Association 91*(6), 2929–2957.

Liu, S. and Y. Su (2022, 03). The Geography of Jobs and the Gender Wage Gap. *The Review of Economics and Statistics*, 1–27.

Mankart, J. and R. Oikonomou (2017). Household search and the aggregate labour market. *Review of Economic Studies 84*(4), 1735–1788.

Manning, A. (2003). *Monopsony in Motion*. Princeton: Princeton University Press.

Manning, A. (2011). Imperfect competition in the labor market. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 4, Chapter 11, pp. 973–1041. Elsevier.

Manning, A. and F. Saidi (2010). Understanding the gender pay gap: What's competition got to do with it? *Industrial and Labor Relations Review 63*(4), 681–698.

Mas, A. and A. Pallais (2017). Valuing alternative work arrangements. *American Economic Review 107*(12), 3722–3759.

McGee, A., P. McGee, and J. Pan (2015). Performance pay, competitiveness, and the gender wage gap: Evidence from the United States. *Economics Letters 128*(C), 35–38.

Niederle, M. and L. Vesterlund (2007). Do women shy away from competition? do men compete too much? *Quarterly Journal of Economics 122*(3), 1067–1101.

Nishiyama, S. (2019). The joint labor supply decision of married couples and the U.S. social security pension system. *Review of Economic Dynamics 31*, 277–304.

Ortigueira, S. and N. Siassi (2013). How important is intra-household risk sharing for savings and labor supply? *Journal of Monetary Economics 60*, 650–666.

Pekkarinen, T. and J. Vartiainen (2006). Gender differences in promotion on a job ladder: Evidence from Finnish metalworkers. *Industrial and Labor Relations Review 59*(2), 285–301.

Pilossoph, L. and S. L. Wee (2021). Household search and the marital wage premium. *American Economic Journal: Macroeconomics 13*(4), 55–109.

Ransom, M. and R. L. Oaxaca (2005). Intrafirm mobility and sex differences in pay. *Industrial and Labor Relations Review 58*(2), 219–237.

Ransom, M. R. and R. L. Oaxaca (2010). New market power models and sex differences in pay. *Journal of Labor Economics 28*(2), 267–289.

Redmond, P. and S. McGuinness (2019). The gender wage gap in Europe: Job preferences, gender convergence and distributional effects. *Oxford Bulletin of Economics and Statistics 81*(3), 564–587.

Redmond, P. and S. McGuinness (2020). Explaining the gender gap in job satisfaction. *Applied Economics Letters 27*(17), 1415–1418.

Staiger, D. O., J. Spetz, and C. S. Phibbs (2010). Is there monopsony in the labor market? Evidence from a natural experiment. *Journal of Labor Economics 28*(2), 211–236.

Sulis, G. (2011). What can monopsony explain of the gender wage differential in Italy? *International Journal of Manpower 32*(4), 446–470.

Sullivan, P. and T. To (2014). Search and non-wage job characteristics. *Journal of Human Resources 49*(2), 472–507.

Sánchez, R., J. Finot, and M. G. Villena (2022). Gender wage gap and firm market power: Evidence from Chile. *Applied Economics 54*(18), 2109–2121.

Valletta, R. G. (2018). Recent flattening in the higher education wage premium: Polarization, skill downgrading, or both? In *Education, Skills, and Technical Change: Implications for Future U.S. GDP Growth*, pp. 313–342. National Bureau of Economic Research.

Wang, H. (2019). Intra-household risk sharing and job search over the business cycle. *Review of Economic Dynamics 34*, 165–182.

Webber, D. A. (2016). Firm-level monopsony and the gender pay gap. *Industrial Relations 55*(2), 323–345.

Wiswall, M. and B. Zafar (2017). Preference for the workplace, investment in human capital, and gender. *Quarterly Journal of Economics 133*(1), 457–507.

Wu, C. and D. Krueger (2021). Consumption insurance against wage risk: Family labor supply and optimal progressive income taxation. *American Economic Journal: Macroeconomics 13*(1), 79–113.

Xiao, P. (2024). Equilibrium sorting and the gender wage gap. Discussion paper, Duke University.

Yeh, C., C. Macaluso, and B. Hershbein (2022). Monopsony in the US labor market. *American Economic Review 112*(7), 2099–2138.

Web Appendix to 'Gender gaps in pay and inter-firm mobility'

A Appendix to basic model

A.1 Dynamic monopsony representation

Here I, present the firm problem in the style of the dynamic monopsony model of the labor market (Manning, 2003). Group-specific inflow (recruiting) and outflow (quit) rates depend on offered wage rates and are denoted by $q_g(w_g)$ and $r_g(w_g)$, respectively, where I suppress a firm index for convenience. It is an important contribution of my paper that I have derived the functions $q_g(w_g)$ and $r_g(w_g)$ as endogenous equilibrium objects in Section 2.6.

Group-specific employment at a firm evolves according to

$$n_{g,t} = (1 - q_g(w_{g,t}))\, n_{g,t-1} + r_g(w_{g,t}).$$

In a steady state where the number of quits equals the number of recruits, $q(w_g) = r_g(w_g)$, labor supplied by group g to the considered firm is given by

$$n_g = \frac{r_g(w_g)}{q_g(w_g)}.$$

Steady-state profits obtained from employing workers of group g are

$$(a_g - w_g) \cdot \frac{r_g(w_g)}{q_g(w_g)} \cdot h_g,$$

where a_g is the marginal revenue product and h_g are hours worked per worker. Profits are maximized by wage offer

$$w_g = \alpha_g \cdot \frac{1}{1 + 1/\eta_g} \tag{A.1}$$

where

$$\eta_g = \frac{r_g' w_g}{r_g} - \frac{q_g' w_g}{q_g}$$

is the elasticity of the number of workers who supply their labor to a given individual firms which is the sum of the (absolute) elasticities of recruits and the quit rate.

A.2 Alternative derivation of firm-level labor-supply elasticity

In this appendix, I derive the elasticity of labor supply to individual firms in a way that puts front and center worker flows between firms and, in particular, workers' quit decisions. For this, I slightly change the distribution of worker preferences over non-pay job characteristics and use a way similar to Bhashkar and To (2003). This change allows an easy representation of workers' firm choices in the spirit of the empirical analysis while it yields the same results regarding the firm-level labor-supply elasticity as the baseline model.

Here, the non-pay characteristics of a job are mapped into a scalar v on the unit circle, like in a Salop model of product market competition. There are V firms with actual characteristics described by $v = 0,\ {}^1\!/_V,\ {}^2\!/_V,\ \ldots,\ 1$. Each worker is assigned a number which summarizes his or her ideal employer and these worker ideals are distributed uniformly on (0,1). Worker utility depends on the difference between his or her ideal workplace and the actual characteristics of the chosen employer. Specifically, the household target function is

$$u = \log c + \frac{1}{\gamma_f} \cdot (1 - |k_f - v_f|) + \frac{1}{\gamma_m} \cdot (1 - |k_m - v_m|)\,, \tag{A.2}$$

where k_g describes non-pay characteristics of the chosen firm, and v_g the worker's most preferred job characteristics.

To derive the elasticity of labor supply to individual firms, I consider the $\bar{n}_g$ workers who work for a given firm and evaluate how many of these workers would change employer if the firm were to change its wage offer by factor z. Each worker compares the costs of staying with the firm and the costs Γ_g of switching to another firm,

$$z \cdot w_g \cdot h_g \cdot \lambda \gtrless \Gamma_g.$$

The staying costs on the left-hand side reflect the absolute reduction in earnings, i.e., share z of labor earnings $w_g h_g$, which are translated into utility terms through multiplication with the marginal utility of wealth, i.e., the Lagrange parameter on the budget constraint, λ. The switching costs on the right-hand side capture the differences in utility from non-pay job characteristics between the current employer and the firm one would switch to (the utility value of a change in job attributes) and are here summarized by Γ_g which will be related to deep parameters of the model later. The share of workers who would switch to another firm is the share of workers for whom these quitting costs are less than $z \cdot w_g \cdot h_g \cdot \lambda$. The resulting number of workers who would remain at the firm after the pay cut is

$$n_g = \bar{n}_g \cdot \left(1 - \mathrm{cdf}_{\Gamma,g}\left(z \cdot w_g \cdot h_g \cdot \lambda\right)\right),$$

where $\mathrm{cdf}_{\Gamma,g}$ is the group-specific cumulated distribution function of quitting costs. Since z is the *relative* pay *cut*, the elasticity of labor supply to the individual firm is given by

$$\eta_g = -\frac{n_g}{z} \cdot \frac{1}{\bar{n}_g} = w_g \cdot h_g \cdot \lambda \cdot \mathrm{pdf}_{\Gamma,g}\left(z \cdot w_g \cdot h_g \cdot \lambda\right),$$

where $\mathrm{pdf}_{\Gamma,g}$ is the density function of switching costs among workers in the firm.

In a symmetric equilibrium, it is straightforward to determine the distribution of quitting costs Γ_g. The indifferent worker is located exactly in the middle between the two relevant firms and hence has zero non-pecuniary costs of switching between the two firms. On the other extreme, for the worker whose ideal workplace is exactly matched by the considered firm, switching to the next best firm is associated with a reduction of utility from non-pay job attributes by $1/(\gamma_g V)$. Hence, switching costs are distributed uniformly on $(0, {}^1\!/_{\gamma_g V})$ such that the density is constant and given by $\gamma_g V$. It follows that $\eta_g = w_g \cdot h_g \cdot \lambda \cdot \gamma_g \cdot V$. Combining this result with the budget constraint and $\lambda = c^{-1}$ with log utility gives the firm-level labor-supply elasticity by workers of gender g as

$$\eta_g = \gamma_g \cdot V \cdot \frac{w_g h_g}{w_g h_g + w_{-g} h_{-g}}. \tag{A.3}$$

Hence, this model version delivers the same result for η_g as the one from the main text.

A.3 Search costs

In my baseline model, there are no monetary quitting costs. Workers can react to pay cuts by instantaneously switching to another firm and potential losses in utility from non-pay job characteristics are the only cost of doing so. In this Appendix, I introduce an additional, fixed cost of quitting and show that this extension, while complicating the derivations, does not impact on gender-specific elasticities of labor supply to individual firms beyond a uniform rescaling of the preference parameters γ_f and γ_m. For convenience, I perform this extension within the framework set up in Appendix A.2.

I assume that, when quitting at an employer, an individual has to pay an additional (search) cost of Ω (expressed in utils) before being able to sign up at a new firm. I still allow workers to move to their (now) most preferred firm, so a way of interpreting Ω is as the cost of (perfectly directed) search. In the following, I suppress indices for convenience but Ω can be thought of being gender-specific. An individual now quits at a wage-cutting firm if

$$z \cdot w \cdot h \cdot \lambda > \Gamma + \Omega.$$

Hence, the quit rate is $q = \mathrm{cdf}_{\Gamma+\Omega}\left(z \cdot wh \cdot \lambda\right)$ and the firm-level labor-supply elasticity is

$$\eta = \frac{\partial q}{\partial z} = \mathrm{pdf}_{\Gamma+\Omega} \cdot wh \cdot \lambda.$$

Two aspects are worth noting about the above result. First, while Γ varies across individuals of a given gender, Ω is a fixed cost of quitting and hence a (gender-specific) constant. Second, in this version, the smallest value of Γ is negative in equilibrium. There are workers who have experienced a small change in their job preferences which would make them better off at a different firm but they stay at their previous employer to avoid the monetary quitting costs Ω. The indifferent worker prior to any pay cut is characterized through $\Gamma + \Omega = 0$ (rather than $\Gamma = 0$ as in the baseline model) such that the slightest pay cut z induces some workers to quit.

To determine the density function of total quitting costs, $\text{pdf}_{\Gamma+\Omega}$, in equilibrium (where further pay cuts do not pay off for firms, i.e., at $z = 0$), one can concentrate on the group of workers for whom a marginal pay cut may induce quitting. These are the workers who would work for a different firm were it not for the fixed quitting costs Ω. For a firm j at location v in the job-characteristics space, these workers are located between $v - 1/(2V) - \gamma\Omega/2$ and $v - 1/(2V)$ as well as between $v + 1/(2V)$ and $v + 1/(2V) + \gamma\Omega/2$. In these intervals, workers would not work for the considered firm if Ω were zero but, for positive Ω, those who previously worked for the firm remain also after their job preferences have shifted into these intervals (share $1/V$ of the workers in these intervals). Thus, mass $\gamma\Omega/V$ of workers work for firm j because of the fixed quitting costs (share $\gamma\Omega$ of the firm's total workforce which is still $1/V$ in equilibrium). Within this group, the smallest value of total quitting costs is zero (the worker for whom $\Gamma = -\Omega$) and the largest is Ω (the worker for whom $\Gamma = 0$) and total quitting costs are distributed uniformly with density $1/\Omega$. Combined with share $\gamma\Omega$ of all workers at the firm falling in this group. The density of total quitting costs among all workers in the firm evaluated at zero is

$$\text{pdf}_{\Gamma+\Omega}(0) = \gamma.$$

Hence, the equilibrium firm-level labor-supply elasticity in this model version is

$$\eta = \gamma wh\lambda = \gamma whc^{-1}$$

which differs from its counterpart in the baseline model only in the absence of the constant V. It follows that in a calibrated version of this model version targeting gender-specific values for η, the values of the preferences parameter γ_f and γ_m would be rescaled but the gender gap in them, $\Delta\gamma = \log\gamma_m - \log\gamma_f$ would remain the same. Also any multiplicative change in γ_f as performed in the counterfactuals presented in Section 4 would have identical effects across model versions.

A.4 Testable prediction

The empirical analysis centers on the relation between wages and quits. In my model, better paying firms employ more workers and are also less likely to be left by workers who experience a change in non-pay job preferences.[27]

In the simple environment of the basic model, I can derive quit probabilities and the results of quit regressions analytically. Workers quit when their new non-pay job preferences differ sufficiently from their old ones while what is sufficient depends on pay differences between the current and potential new employer. From the perspective of a firm, this means that higher pay not only attracts more workers but also reduces the share of current workers who quit. Formally, the share of workers of group g that leaves firm j between the preceding and the current period is given as the fraction of workers who draw now job-specific preferences, θ, multiplied by the fraction of those workers who afterwards prefer to work for a different firm, $1 - n_{g,j}$. The latter fraction is smaller for firms that pay higher wages. Thus,

$$q_{g,j}(w_{g,j}) = \theta \left(1 - n_{g,j}(w_{g,j})\right)$$

Using a first-order Taylor approximation in logs, this expression can be rearranged to equation (13) in the main text.

[27] In the quantitative analysis performed in Section 4, I consider firm-specific productivity shocks with autocorrelation ρ such that log productivity of gender g at firm j is given by $\log a_{g,j,t} = (1-\rho)\log a_g + \rho \log a_{g,j,t-1} + \xi_{j,t}$, where $\xi_{j,t}$ is the productivity innovation to firm j in period t. With persistent productivity shocks, a firm that pays high wage rates this period also tends to do so in the next period and is therefore less likely to be left. For this reason, future quits are linked to current wage rates.

B Appendix to empirical analysis

B.1 Variable definitions

Quits. I first construct separations. A separation between years t and $t+1$ occurs when either the individual was employed in year t but not in year $t+1$ or the individual was employed in both years t and $t+1$ and reports a tenure of one year or less in year $t+1$. A quit is a voluntary separation which I define based on the answer to the question "Why did your last job end?". If the answer is "quit; resigned; retired; pregnant; needed more money; just wanted a change in jobs; was self-employed", I treat the separation as voluntarily induced by the worker. While all other reasons ("Company folded/changed hands/moved out of town; employer died/went out of business", "Strike; lockout", "Laid off; fired"; "Other; transfer; any mention of armed services", "Job was completed; seasonal work; was a temporary job") leads to the separation being classified as involuntary. When information on the reason why the last job ended is missing, I treat separations into unemployment as involuntary and separations into employment or out of labor force as voluntary. The question why the wife's last job ended was asked continuously from 1979 on. This allows me to construct continuous series of quits for husbands and wives from 1978 on.

Labor earnings. The PSID reports labor income including wages and salaries, bonuses, overtime pay, tips, commissions and the like but excluding business income and farm income. To this variable, I add for each individual business income and half the household's farm income. I deflate labor income to 1983 dollars using the CPI.

Hours worked. I use total annual work hours on all jobs including overtime as provided in the PSID (weeks worked times weekly hours plus overtime hours).

Hourly wage rate. I determine the average hourly wage rate of an individual as yearly labor earnings divided by yearly hours worked.

Contributed earnings share. I calculate the contributed earnings share as own labor earnings divided by the sum of one's own and the partner's labor earnings.

Year. I use year dummies to indicate years. For detrending issues, I construct a variable that runs from 1 in the first year of my main sample (1978) to 19 in the last year (1996).

Age. I use a full set of dummies for age measured in years.

Education. I use dummy variables for the following six education categories: "less than 9 years of schooling", "9 - 11 grades; some high school; junior high", "12 grades; high school", "12 grades plus non-academic training or College, no degree", "College degree, no advanced degree mentioned", "College, advanced or professional degree".

Race. I use dummies indicating white and non-white individuals, respectively.

Region. I use dummies for the four major Census regions: West (Alaska, Washington State, Oregon, Idaho, Montana, Wyoming, California, Nevada, Utah, Colorado, Arizona, New Mexico, Hawaii), Midwest (North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, Indiana, Michigan, Ohio), South (Texas, Oklahoma, Arkansas, Louisiana, Kentucky, Tennessee, Mississippi, Alabama, West Virginia, Maryland, Delaware, Washington DC, Virginia, North Carolina, South Carolina, Georgia, Florida), and Northeast (Maine, New Hampshire, Vermont, Massachusetts, Connecticut, Rhode Island, New York, Pennsylvania, New Jersey).

Children. I use dummy variables for the following 6 categories: no child, 1 child, 2 children, 3 children, 4 children, 5 or more children.

Industry. I use dummies for the 12 major industry groups "Agriculture, Forestry, and Fisheries", "Mining", "Construction", "Manufacturing", "Transportation, Communications, and Other Public Utilities", "Wholesale and Retail Trade", "Finance, Insurance, and Real Estate", "Business and Repair Services", "Personal Services", "Entertainment and Recreation Services", "Professional and Related Services", "Public Administration".

Occupation. I use dummies for the following 12 major occupation groups "Professional, Technical, and Kindred Workers", "Managers and Administrators, except Farm", "Sales Workers", "Clerical and Kindred Workers", "Craftsman and Kindred Workers", "Operatives, except Transport", "Transport Equipment Operatives", "Laborers, except Farm", "Farmers and Farm Managers", "Farm Laborers and Farm Foremen", "Service Workers, except Private Household", "Private Household Workers".

Tenure. I use eleven dummy variables for 0, 1, ..., 9, 10 and more years of tenure.

B.2 Sample selection

The sample selection is similar to the one in Bredemeier et al. (2019). I select a sample of married spouses aged 20 to 65 with male household heads. I drop the sample of economic opportunity (SEO) which is not representative for the U.S. population.

In order to handle outliers and data errors, I drop household-year observations where an individual's age falls or increases by more than two years from one year to the next, an individual's wage rate or hours worked increase by more than 250% or fall by more than 40% between two years, where an individual works more than 93 hours on average per week, or where an individual's hourly wage rate falls into the top 0.5% of the distribution.

I reshape the data to a sample of jobs with information on pay, hours, subsequent separation and the worker's socio-economic, demographic, and family background. I disregard jobs held by women whose husbands do not work in the considered year. The final sample consists of about 40,000 jobs held by married spouses. Table 8 summarizes some descriptive statistics about the final sample.

B.3 Regression specifications

Table 2: *Columns (1) and (2):* Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times year, log hourly

Table 8: Descriptive statistics.

	jobs held by men	jobs held by women
N	20,231	20,131
separation	0.1982	0.2439
quit	0.0844	0.1203
hourly wage rate	11.23	7.59
yearly hours worked	2261.8	1604.4
contributed earnings share	0.6695	0.3371

Notes: Hourly wage rate in 1983 dollars.

wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Columns (3) and (4): Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Table 3: *Row i:* Dependent variable of the second stage: Quit. Independent variables of the second stage: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies (for women only). Dependent variable of the first stage: contributed earnings share (including in its interaction with the log wage rate). Independent variables of the first stage: partner's age dummies, partner's education dummies, partner's occupation dummies, partner's race dummies, children dummies (for men only). Estimated with 2SLS.

Row ii: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS for a restricted sample of individuals with a positive number of children.

Row iii: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times number of children, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Row iv: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS for a restricted sample of individuals who remain in the labor force in year $t + 1$.

Table 4: *Row i:* Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with probit.

Row ii: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with logit.

Row iii: Dependent variable: Quit. Independent variables: Log hourly wage rate, square of log hourly wage rate squared, cube of log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Row iv: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Row v: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies, age dummies times contributed earnings share, year dummies times contributed earnings share, education dummies times contributed earnings share, region dummies times contributed earnings share, race dummies times contributed earnings share, children dummies times contributed earnings share. Estimated with OLS.

Row vi: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies, tenure dummies. Estimated with OLS.

Row vii: Dependent variable: Quit. Independent variables: Log hourly wage rate, contributed earnings share, log hourly wage rate times contributed earnings share, log hourly wage rate times year, log hourly wage rate times year squared, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated as (individual) fixed-effect regression.

Table 5: *Row i:* Dependent variable: Quit. Independent variables: Log hourly wage rate, log own labor earnings (+1 for women), log hourly wage rate times log own labor earnings (+1 for women), log hourly wage rate times year, log hourly wage rate times year squared,

age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Row ii: Dependent variable: Quit. Independent variables: Log hourly wage rate, square of log hourly wage rate, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Row iii: Dependent variable: Quit. Independent variables: Log hourly wage rate, log yearly hours worked (+1 for women), log hourly wage rate times log yearly hours worked (+1 for women), log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Row iv: Dependent variable: Quit. Independent variables: Log hourly wage rate, partner's log labor earnings (+1 for women's earnings), log hourly wage rate times partner's log labor earnings (+1 for women's earnings), log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

Row iv: Dependent variable: Quit. Independent variables: Log hourly wage rate, sample average of own and partner's labor earnings, log hourly wage rate times sum of sample average of own and partner's labor earnings in hundred thousand 1983 dollars, log hourly wage rate times year, log hourly wage rate times year squared, age dummies, year dummies, education dummies, region dummies, race dummies, children dummies. Estimated with OLS.

C Appendix to quantitative model analysis

C.1 Additional model features

Horizontal differences in the degree of labor-market competition are modelled as differences in the scale parameter of the distribution that governs workers' non-pay preferences over firms, $1/V_z$ where z indicates the horizontal segments of the labor market. An interpretation of these differences is that some labor markets are more concentrated such that there are fewer firms and the non-pay differences between any two firms is larger. Further, vertical differences in workers' marginal revenue product are achieved by segment-specific multiplicative productivity shifters α_y where y indicates the vertical levels of the labor market. An interpretation is that workers with more schooling work on higher levels of the hierarchy within a firm and are more productive. When calibrating my model, I follow the interpretation of V_z and α_y as firm concentration in an industry and productivity differences between workers with different education, respectively.

To model preferences over labor-market segments, I add further taste shifters, $\epsilon_g(y_g, z_g)$, to utility that reflect the level of utility a worker obtains directly from working in a specific segment of the labor market. Also here, I assume that taste shifters are type-I extreme-value distributed and denote the scale parameter by $\sigma.$, i.e., the marginal revenue product of a worker is determined by the individual-specific a_i and the segment-specific α_z and given by $\alpha_z \cdot a_i$.

The endogenous hours choice is modeled by subtracting a standard convex iso-elastic function in hours from utility. Specifically, instead of (1), household preferences are now described by

$$\begin{aligned} u = &\log c - \frac{1}{\nu_f} \cdot \frac{h_f^{1+1/\psi}}{1+1/\psi} - \frac{1}{\nu_m} \cdot \frac{h_m^{1+1/\psi}}{1+1/\psi} \\ &+ \frac{1}{\gamma_f} \cdot \varepsilon_f\left(k_f\right) + \frac{1}{\gamma_m} \cdot \varepsilon_m\left(k_m\right) + \frac{1}{\gamma_f} \cdot \epsilon_f(y_f, z_f) + \frac{1}{\gamma_m} \cdot \epsilon_f(y_m, z_m), \end{aligned} \tag{C.1}$$

which also includes the direct utility workers achieve from their horizontal and vertical labor-market choices, ϵ_g. In (C.1), ψ is the Frisch elasticity of labor supply to the market and ν_f and ν_m are the inverse weights on disutility from work.[28]

Since the quantitative model has an intensive margin at which labor supply reacts to wage rates, firms take this into account when deciding upon wage offers. I assume that firms compete for workers in terms of short-run wages. Put differently, an equilibrium is a situation where a unilateral deviation in pay for one period does not pay off to the respective firm.[29] The decisive elasticity for their wage setting is now the elasticity of total hours supplied to the respective firm,

$$\phi = \eta + \psi.$$

The Frisch elasticity governs labor-supply reactions to short-run wage fluctuations because households live forever and have unlimited access to a risk-free bond with interest rate i. Accordingly, the budget constraint of a couple household now is $c + b' = w_f(k_f)\,h_f + w_m(k_m)\,h_m + (1+i)b$, where a prime (') denotes next period. The intertemporal preferences of a household are described by maximizing $U = u + \beta U'$.

In the quantitative model, there is a fraction s of single agents. The remaining fraction $1 - s$ lives in couples. Singles do not have a partner but are otherwise identical to spouses in couples. A single of gender g has period utility

$$u_g = \log c_g - \frac{2}{\nu_g} \cdot \frac{h_g^{1+1/\psi}}{1+1/\psi} + \frac{2}{\gamma_g} \cdot \varepsilon_g(k_g) + \frac{2}{\gamma_g} \cdot \epsilon_g(y_g, z_g) \tag{C.2}$$

and acts subject to $w_g = w_g(k_g)$ and $c_g + b'_g = w_g \cdot h_g + (1+i)b_g$. The factors 2 in the preference weights reflect that singles assign full weight to their own labor disutility and non-pay job utility. Couple households only weigh both factors by 50% for each spouse and hence maximize the average utility of their members, see (C.1). This does not affect consumption, which is household-public.

[28] I allow for gender differences in the Frisch elasticity in Appendix C.6

[29] In Appendix C.6, I also consider the case of competition in permanent wages which delivers similar results.

C.2 Technical assumptions and equilibrium conditions

Technical assumptions. Apart from non-pay job preferences, I consider all heterogeneity to be binary such that there are $2^7 = 128$ combinations of a married worker's gender g, productivity x, horizontal position y, and vertical position z as well as productivity $-a$, horizontal position $-y$, and vertical position $-z$ of the partner. Singles simply differ in their own gender, productivity, horizontal position, and vertical position such that there $2^4 = 16$ different groups of singles. There is hence a total of $2^7 + 2^4 = 144$ different groups of workers on the labor market. Within these groups, workers differ in their preferences over workplaces as described in Section 2.

As a technical assumption, I assume that workers take their vertical and horizontal choices before learning specific firms' non-pay job characteristics within the segments. This rules out that workers choose a particular segment of the labor market because there is a particular firm in this segment with very likable job characteristics. Instead, workers take into account the expected utility from entering a specific segment which they can assess from the information they have about the segment. Further, this assumption implies that individual firms cannot attract specific workers into their segment. Rather, it is overall pay in the segment which influences workers' choices of segment. In line with Section 2, I assume that firms do not internalize the effect of their individual pay on the size of their segment.

I assume that firms within a segment can observe a worker's gender and marital status as well as which segment the partner works in but not the exact preferences over workplaces (as in Section 2). This implies that firms can condition pay on marital status and on partner characteristics. Hence, there are 144 different wage rates in the economy, one for each of the 144 cells discussed above. The structure of the model implies that the equilibrium wage rate within each cell does not depend on cell size which allows me to solve for the within-cell equilibrium and the selection of individuals into the cells separately.

In order to maintain this important property, I leave out from the quantitative model a number of aspects that are further discussed in the context of imperfect competition on the labor market and gender differences in labor-market outcomes. Instead, I address them in a model version that does not feature within-gender heterogeneity apart from non-pay job preferences. Appendix C.6 presents further model extensions that include gender differences in the elasticity of labor supply to the market, home production, firm entry, and alternative forms of wage competition between firms. I perform the main counterfactuals also within these model versions and compare results to those obtained from the baseline model with and without within-gender heterogeneity. The results show that, while some of the aspects affect the *level* of, e.g., wage rates to a non-negligible degree, gender *gaps*, which are the focus of this paper, behave very similarly across model versions which justifies abstracting from the discussed aspects in the main quantitative model.

Formal summary of equilibrium conditions. The quantitative model consists of 144 cells and households' self-selection into these cells. A cell is defined by worker's gender, marital status, and productivity, their choice of vertical and horizontal labor-market segment, and - for married individuals - productivity and vertical and horizontal labor-market segment of the partner.

The within-cell steady-state equilibrium is described as follows. In cell $p = \{g, x, y, z, -x, -y, -z\}$ which includes married individuals with gender g, productivity x, vertical position y, and horizontal position z, as well as the partner's productivity $-x$, vertical position $-y$, and horizontal position $-z$, the following conditions describe the steady state,

$$w_p = a_x \cdot \alpha_y \cdot \frac{1}{1 + 1/\phi_p}, \tag{C.3}$$

$$\phi_p = \gamma_g \cdot V_z \cdot w_p h_p / (w_p h_p + w_{-p} h_{-p}) + \psi, \tag{C.4}$$

$$h_p^{1/\psi} = \nu_g \cdot c_p^{-1} \cdot w_p, \tag{C.5}$$

$$c_p = w_p h_p + w_{-p} h_{-p}, \tag{C.6}$$

where $-p = \{-g, -x, -y, -z, x, y, z\}$ describes the partner's cell. Conditions (C.3) to

(C.6) describe, respectively, firms' profit-maximizing wage offers, the elasticity of total hours worked (combining extensive and intensive margin), the first-order condition for hours worked, and the steady-state household budget constraint.

In cell $n = \{g, x, y, z\}$ that includes single individuals with gender g, productivity x, vertical position y, and horizontal position z, the steady state is described by

$$\begin{aligned}
w_n &= a_x \cdot \alpha_y \cdot \frac{1}{1 + 1/\phi_n}, \\
\phi_n &= \gamma_g/2 \cdot V_z + \psi, \\
h_n^{1\psi} &= \nu_g/2 \cdot c_n^{-1} \cdot w_n, \\
c_n &= w_n h_n.
\end{aligned}$$

Type-I EV distributed taste shifters allow to determine cell choices as follows. Among a group of married individuals with exogenous characteristics g, x, and $-x$, feasible cell combination p', $-p'$ is chosen by share

$$s_{p',-p'} = \frac{\exp(\widetilde{u}_{p',-p'}/\sigma)}{\sum_P \exp(\widetilde{u}_{p,-p}/\sigma)},$$

where $\widetilde{u}_p$ is household utility (as described by (C.1)) net of taste shifters and P is the set of feasible choices for the considered type of couple. Analogously, among a group of single individuals with exogenous characteristics g and x, feasible cell p is chosen by share

$$s_n = \frac{\exp(\widetilde{u}_n/\sigma)}{\sum_N \exp(u_n/\sigma)},$$

where $\widetilde{U}_n$ is utility (as described by (C.2)) net of taste shifters and N is the set of feasible choices for the group.[30] The overall share of workers in a particular cell is obtained by multiplying s_n and s_p respectively, with the share of workers that have the particular characteristics which gives $s_p \cdot (1 - s) \cdot s_g^x \cdot s_{-g}^{-x}$ and $s_n \cdot s \cdot s_g^x$ where s is the singles share and s_g^x is the share of workers with gender g who have productivity x.

[30] It is sufficient to consider the expected value of period utility here since also the direct utility gains or losses from choosing a specific segment accrue every period.

C.3 Calibration

The parametrization of the model is a combination of setting some parameters and calibrating others and targets the present-day U.S. economy. It is summarized in Table 9. I set the share of couple households to its empirical value of 0.7. The Frisch elasticity of labor supply to the market is set to 0.5 in accordance with Domeij and Flodén (2006).[31] The time preference rate is set to 0.98 to achieve a two percent real interest rate, interpreting a period as one year. The share of workers for whom preferences are redrawn each period is set to 0.2 mimicking a separation rate of close to 20%.[32] I consider an AR(1) process for firm-specific log productivity and take its persistence and standard deviation (0.97 and 0.09, respectively) from Bachmann and Bayer (2009).[33]

Gender-specific utility weights and productivity distributions are chosen to match the BLS estimates for the gender gap in average wage rates and average earnings for 2015, $\Delta w = 19.9$ log points and $\Delta wh = 32.6$ log points, and gender-specific average elasticities of labor supply to individual firms of $\eta_f = 1.793$ and $\eta_m = 2.413$ which are the estimates from Ransom and Oaxaca (2010) for their most recent sample. Normalizing the average female wage rate to $\bar{w}_f = 1$ and average hours worked to $\bar{h} = 0.33$, the targeted gaps imply $\bar{w}_m = 1.22$, $\bar{h}_f = 0.31$, and $\bar{h}_m = 0.35$. I normalize the low productivity level to 1 and the male share with high productivity to 0.5 and achieve the targets by setting the high productivity level to 2.06, the female high productivity share to 0.32, and the inverse labor disutility weights to $\nu_f = 0.038$ and $\nu_m = 0.041$. The average elasticities of labor supply to individual firms are matched by setting the inverse utility weights on non-pay job attributes to $\gamma_f = 0.417$ and $\gamma_m = 0.441$.

[31] I eschew gender differences in the Frisch elasticities. This is due to a combination of two points. First, I want to limit the dimensions of exogenous gender differences for the counterfactuals. Second, empirical gender differences in Frisch elasticities are likely limited once estimation biases are accounted for (Bredemeier et al. 2019). Note that the model features endogenous gender differences in uncompensated (Marshallian) labor-supply elasticities due to weaker income effects for married women compared to married men.

[32] I use annual quit rates for the total economy from the BLS, see https://www.bls.gov/news.release/jolts.t18.htm.

[33] I vary the parameters of the process for firm-specific productivity in Appendix C.4.

Table 9: Parameter values.

Symbol	Interpretation	Value	Target/Source
Aggregate parameters			
s	share of couples	0.700	observed
ψ	Frisch elasticity (to market)	0.500	Domeij and Flodén (2006)
σ	scale parameter taste shifters	0.516	college share
β	time preference rate	0.980	real interest rate
θ	share re-drawn job preferences	0.111	average quit rate
ρ	persistence firm-productivity shocks	0.995	Bachmann and Bayer (2009)
σ_a	std. dev. firm-productivity shocks	0.12	Bachmann and Bayer (2009)
Parameters governing within-gender heterogeneity			
a_x	productivity level		
	high	2.055	normalize
	low	1.000	$\bar{w}_f = 1$
α_y	marginal revenue product shifter		
	high position	1.333	college
	low position	0.667	wage premium
V_z	(inverse) firm concentration		
	industry 1	1.50	80-20 ratio
	industry 2	0.50	firm concentration
Parameters governing exogenous gender differences			
s_g^{high}	share of workers with high productivity		
	female	0.320	wage
	male	0.500	gap
ν_g	inv. utility weight on labor supply		
	female	0.038	hours
	male	0.041	gap
γ_g	inv. utility weight, non-pay attributes		
	female	0.404	gap in inter-
	male	0.430	firm mobility
Implied gender gaps in exogenous factors			
$\Delta\bar{a}$	gap in average productivity	13.3 lp	$\Delta w = 19.9\,\text{lp}$
$\Delta\nu$	gap in labor disutility	9.9 lp	$\Delta h = 12.7\,\text{lp}$
$\Delta\gamma$	gap in weight on non-pay attributes	6.3 lp	$\Delta\eta = 29.7\,\text{lp}$

Notes: $\Delta x = \log x_m - \log x_m$. lp = log points.

I proceed as follows to calibrate the parameters that govern vertical and horizontal differences between labor-market segments interpreting the horizontal dimension of the labor market as industries with varying employer concentration and the vertical dimension as college education with differences in productivity. I first normalize the average value of the scale parameter of the taste shifters to 10 and the average productivity shifter to 1. I set the marginal productivity shifters to two thirds and four thirds which mimics a college to no-college wage ratio of 2 while pertaining an average value of one.[34] I set the scale parameters of the taste shifters to 5 and 15 implying that industry 2 is three times as concentrated as industry 1 in line with most recent observation (2012) of the 80-20 ratio of the C4 concentration index across three-digit manufacturing industries while pertaining an average value of 1.[35] I set the variance of the taste shifters to 0.52 to match an equilibrium share of workers with the high vertical position of two thirds corresponding to the 2015 share of people with more than a high-school degree in the labor force.[36]

My model generates marriage wage premia for men and marriage wage penalties for women because particularly couples are subject to the proposed mechanism that leads to an endogenous gender gap in inter-firm mobility. Quantitatively, the generated marriage premia and penalties are quite reasonable compared to the data and, accordingly, the gender wage gap is smaller among singles and larger among married individuals to a data-consistent degree, see Table 10 in the Appendix. The model also features part-time penalties as the wish to work shorter hours coincides with a particular earner role within the family that makes the specific worker rather immobile between firms which firms can exploit. Quantitatively, empirical part-time penalties are matched quite successfully by the model, see the lower part of Table 10. The good model performance with respect to non-targeted moments provides confidence that the calibrated model is a suitable laboratory for counterfactual analysis.

[34] In 2015, the average hourly wage rate of workers with at most a high-school degree was \$16.96 while it was \$34.07 for workers with a bachelor degree or more (own aggregation based on Valletta, 2018, Table 2).

[35] The C4 index is the market share of the four largest firms in an industry. It is provided by the Census Bureau under the North American Industry Classification System (NAICS) for 1997, 2002, 2007, and 2012. While differences across industries in concentration are important for the model, its level simply affects the calibration of γ_g, see (4).

[36] This number stems from the BLS Spotlight on Statistics "Profile Of The Labor Force By Educational Attainment" from August 2017.

Table 10: Non-targeted moments.

	model	data
married to single wage gap		
among men	5 lp	6 lp
among women	-12 lp	-5 lp
gender wage gap		
among married	25 lp	25 lp
among singles	8 lp	9 lp
part-time to full-time gap		
earnings, among men	138 lp	118 lp
earnings, among women	135 lp	98 lp
wage rates, among men	88 lp	82 lp
wage rates, among women	86 lp	64 lp

Notes: Married-single gaps and gender gaps by marital status (age controlled) from Killewald and Lundberg (2017) and Cheng (2016). Part-time to full-time gaps by population group calculated from the BLS's 'Labor Statistics from the CPS', Tables 37 and 38 and the BLS's chart 'Time spent working by full- and part-time status, gender, and location'. In the model, I define part time in a way identical to the BLS definition, i.e., working 35 hours or less per week where I define $\bar{h}_m$ to correspond to 40 hours per week. lp = log points.

C.4 Quit regressions in the model

While all other model evaluations only consider steady states, the quit regressions presented in Table 11 use a simulation of the model around its steady state. For this, I proceed as follows. I first solve for the steady state as described at the end of Section C.1. This gives data for the steady-state values of wage rates, hours and marginal utility in the different cells of my model as well as cell sizes. I then simulate data as follows. I draw realizations of the idiosyncratic productivity process for each of the 20 firms, 5 in industry 1 and 15 in industry 2, for 219 periods (thus creating 19 periods of data an in my PSID analysis, after cutting 200 burn-in periods).

For each cell, I then first determine pay of every individual firm given their realized wage processes. This is simple because of the abstraction from strategic interaction and the fact that the composition of the workforce is constant within a cell (there are shocks to non-pay job preferences but, due to the law of large numbers, the distribution of these preferences is constant). I then simulate preferences for N workers where N is the share of married workers of the considered gender in this cell times the average annual sample size of my empirical data set. For each worker, I first draw initial preferences from the type-I EV distribution and then, for every period, draw workers for a re-assignment of preferences with probability θ. When drawn for re-assignment, they obtain new draws from the type-I EV distribution.

Based on simulated wage rates offered by the different firms and non-pay preferences of the sampled individuals, firm choices can be obtained as follows. I first calculate labor earnings that the worker would generate at each potential firm and translate it into utils through multiplication with the steady state marginal utility of wealth. To this I add non-pay job utility and determine the maximum of the sum. This gives time series of wage rates and chosen firms for each simulated individual. I combine the data for the different simulated individuals from the different labor-market cells to a panel data set which I then use to run quit regressions. I repeat simulation and subsequent estimation 10,000 times in a

Table 11: The wage sensitivity of quits in artificial data from simulated model.

	(1) **men**	**(2)** **women**	**(3)** **men**	**(4)** **women**
log wage rate	-0.0488^{***}	-0.0285^{***}	-0.0661^{***}	-0.0658^{***}
	(0.0034)	(0.0031)	(0.0037)	(0.0043)
log wage rate			-0.1404^{***}	-0.1481^{***}
$\times$ (earnings share-0.5)			(0.0106)	(0.0115)
observations	20197	20197	20197	20197

Notes: Mean estimates and standard errors from 10,000 Monte-Carlo repetitions. Dependent variable: quit between observation year and following year; linear probability models; standard errors in parentheses; *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$; alternative wage determinant (X): mean wage in respective cell p; additionally included variables: constant, earnings share.

Monte-Carlo style exercise. For my baseline calibration, the results are shown in Table 11.

Qualitatively, the results resemble the empirical ones presented in Table 2. Also for the simulated model data, standard quit regressions without taking into account household earner roles suggest that men are considerably more mobile between firms than women. Hence, quit regressions are able to detect gender differences in inter-firm mobility in the simulated data. Further, the size of the coefficients in the first two columns of Table 11 are of similar magnitude to the ones in Table 2 indicating that the model features a realistic relation between quits and wage rates.

When I include the interaction between the contributed earnings share and the log wage rate, I obtain negative coefficients in the Monte-Carlo lab as I did in the real-world data. In Appendix C.4, I corroborate this finding for alternative calibrations of the firm-specific productivity process. While the coefficients on the interaction terms are somewhat larger than in the empirical results in Table 2, the remaining gender difference in the coefficient on the non-interacted log wage rates are small as are the exogenously fed-in gender differences in the importance of non-pay job characteristics.

Since my baseline calibration features strong autocorrelation of firm-specific productivity, I also performed Monte-Carlo estimations for alternative calibrations. In particular, I also consider the parameter values used in Bachmann and Bayer (2014) and Bachmann et al.

Table 12: Results of quit regressions from simulated data for alternative calibrations of the shock process for firm-specific productivity.

	men	**women**
Baseline calibration	-0.1404^{***}	-0.1481^{***}
$\rho = 0.9950$, $\sigma = 0.1200$	(0.0106)	(0.1481)
Bachmann and Bayer (2014)	-0.3404^{***}	-0.2941^{***}
$\rho = 0.9675$, $\sigma = 0.0905$	(0.0372)	(0.0368)
Bachmann et al. (2013)	-0.7428^{***}	-0.5755^{***}
$\rho = 0.8612$, $\sigma = 0.0472$	(0.0860)	(0.0859)

Mean estimates and standard errors from 10,000 Monte-Carlo repetitions. Dependent variable: quit between observation year and following year; linear probability models; standard errors in parentheses; *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$; alternative wage determinant (X): mean wage in respective cell p; additionally included variables: constant, earnings share.

(2013). My favorite calibration uses the values from Bachmann and Bayer (2009) since they stem from an estimation of a firm-specific productivity process while, for example, Bachmann et al. (2013) use the autocorrelation of sector-specific productivity also for firm-specific productivity. Table 12 shows the most important results, i.e. the coefficients on the interaction term between the log wage rate and the contributed share to household earnings, for the baseline and alternative calibrations. Also for lower values of the autocorrelation, the model predicts a negative coefficient here as is found in the empirical analysis in Section 3.

C.5 Additional counterfactual results

Table 13 reports the levels of gender-specific wage rates, hours worked, and elasticities of labor supply to individual firms in the different model simulations for which gender gaps are reported in Tables 6 and 7.

Table 13: Levels of gender-specific wage rates, hours worked, and elasticities of labor supply to individual firms in the different model simulations.

	w_m	w_f	h_m	h_f	η_m	η_f
Full model (endogenous mobility)						
baseline	1.2195	1.0000	0.3466	0.3051	2.4130	1.7930
$\Delta\nu = 0$	1.2126	1.0072	0.3440	0.3184	2.3709	1.8330
$\Delta\gamma = 0$	1.2167	1.0178	0.3455	0.3064	2.3946	1.9384
$\Delta\nu = 0$ and $\Delta\gamma = 0$	1.2097	1.0250	0.3429	0.3197	2.3524	1.9811
$\Delta a \downarrow 10\,\text{lp}$	1.1982	1.1289	0.3386	0.3139	2.2847	1.9147
$\Delta\nu \downarrow 10\,\text{lp}$	1.2126	1.0073	0.3440	0.3185	2.3706	1.8333
$\Delta\gamma \downarrow 10\,\text{lp}$	1.2151	1.0281	0.3449	0.3071	2.3840	2.0276
Reference model (exogenous mobility)						
baseline	1.2195	1.0000	0.3466	0.3051	2.4130	1.7930
$\Delta\nu = 0$	1.2176	1.0016	0.3444	0.3201	2.4130	1.7930
$\Delta\gamma = 0$	1.2163	1.0720	0.3429	0.3093	2.4130	2.4130
$\Delta\nu = 0$ and $\Delta\gamma = 0$	1.2143	1.0738	0.3407	0.3244	2.4130	2.4130
$\Delta a \downarrow 10\,\text{lp}$	1.2147	1.1097	0.3410	0.3114	2.4130	1.7930
$\Delta\nu \downarrow 10\,\text{lp}$	1.2179	1.0014	0.3448	0.3176	2.4130	1.7930
$\Delta\gamma \downarrow 10\,\text{lp}$	1.2184	1.0246	0.3453	0.3066	2.4130	1.9816

C.6 Extended model versions

In this appendix, I address the following issues: home production, gender differences in elasticities of labor supply to the individual firm, firm entry, and the possibility that competition for workers between firms is performed using permanent rather than period wage rates. To concentrate on the main mechanism that is active within couple households, I do so within a model without singles and that has also no further within-gender inequality beyond non-pay job preferences. In all model versions considered here, I calibrate productivity as well as preference weights on labor supply and non-pay job attributes to match gender gaps in wage rates, hours worked, and inter-firm mobility as in the baseline evaluations, see Section C.3, but for married individuals only. Regarding the gender gap in inter-firm mobility, I use the result of Webber (2016) that the gap is three fifth larger for married individuals.[37] Choices and calibrations for additional model parameters in the different versions are described below. In the following, I describe extended versions of the model and, thereafter, I present and compare results for the different versions.

[37]This gives the following moments to be matched: $w_m = 1.2376$, $w_f = 0.9646$, $h_m = 0.3486$, $h_f = 0.2924$, $\eta_m = 2.6379$, and $\eta_f = 1.6402$.

Benchmark. For comparison, I am evaluating a model that has none of the additional aspects and no within-gender inequality. This model can be understood as the average cell for married individuals in my full quantitative model. It is described by equations (C.3) to (C.6) where the cell index m is identical to the gender index g.

Home production and gender differences in the elasticity of labor supply to the market. In this model version, households additionally produce and enjoy a home good d. The household target function now reads

$$\begin{aligned} u = &\log c - \delta \cdot \log d - \frac{1}{\nu_f} \cdot \frac{(h_f + h_f^h)^{1+1/\psi}}{1+1/\psi} - \frac{1}{\nu_m} \cdot \frac{(h_m + h_m^h)^{1+1/\psi}}{1+1/\psi} \\ &+ \frac{1}{\gamma_f} \cdot (1 - |k_f - v_f|) + \frac{1}{\gamma_m} \cdot (1 - |k_m - v_m|) \,, \end{aligned}$$

where δ is the weight on consumption of the home good and h_g^h are hours worked in home production. The perfect substitutability of market hours and home hours follows Alesina et al. (2011). As shown by Alesina et al. (2011) this preference function endogenously gives rise to gender differences in the Frisch elasticity of labor supply to the market (rather than to the firm). Such gender differences are discussed in the empirical literature with women's labor supply *to the market* usually being found to be more elastic than men's (Keane 2011).

The home production function is Cobb-Douglas with elasticity θ,

$$d = (h_f^h)^{\theta} (h_m^h)^{1-\theta}.$$

I eschew a total factor productivity level in this function as it would not be identified separately from the preference weight δ. I calibrate δ and θ to match empirical home hours by gender.[38] In this model version, I calibrate η (which is the Frisch elasticity of *total* work including housework) to maintain a Frisch elasticity of labor supply *to the market* of 0.5 for men. As an untargeted moment, the Frisch elasticity for women is about 40% larger which lies in the ballpark of gender differences in Frisch elasticities estimated by Bredemeier et al.

[38] Targets are $h_m = 0.1102$ and $h_f = 0.1441$ which are the average weekly hours of unpaid household work of married women and married men from the 2005 PSID expressed as shares of a weekly time endowment of 120 hours.

(2019).[39]

Firm entry. Firms' net profits change in my counterfactual experiments and this may lead to changes in the number of firms. The associated changes in competition may impact on the results. In order to analyze this possibility, I alter the model as follows. I introduce a fixed cost κ which may include, among other things, supervisory labor costs as well as lump-sum fees and taxes. In every period, the number of firms V is determined by free entry total profits are zero,

$$(a_m - w_m)h_m/V - (a_f - w_f)h_f/V - \kappa = 0. \tag{C.7}$$

Note that V impacts on both wage rates and hours. Technically, V becomes an additional endogenous variable and (C.7) an additional equilibrium condition. I calibrate κ to achieve $V = 10$ which is the average number of firms per industry in the full model, see Section C.3.

Permanent-wage competition. In the baseline model, the equilibrium concept imposes that a unilateral change in wage rates within a period does not pay off to any individual firm. One may argue that, in reality, such short-lived pay changes are hard to implement for firms independent of a potential loss of workers to other firms and that competition for workers between firms is rather performed using permanent wage rates. In this model version, I study this possibility. This implies that the elasticity of total labor supply to individual firms (with respect to the permanent wage rate) is now given by

$$\phi_p = \gamma_g \cdot V_z \cdot w_p h_p/(w_p h_p + w_{-p}h_{-p}) + \Psi_p$$

where Ψ_g is the uncompensated (Marshallian) labor-supply elasticity, instead of (C.4). The uncompensated elasticity is endogenously gender-specific and reads

$$\Psi_p = \eta \cdot \frac{1 - e_p}{1 + \eta e_p},$$

[39] Bredemeier et al. (2019) propose and use an estimation method that corrects for estimation biases due to borrowing constraints. They show that methods that suffer from such biases overestimate gender differences in the elasticity of labor supply to the market.

where e_p is the individual's contributed share to household earnings.

Comparing model versions. Table 14 summarizes the main results for the alternative model versions. For each model version, it reports the shares of the endogenous gender gaps which are created without gender differences in preferences and the shares which are to be assigned to the different dimensions of gender differences in preferences (as in Table 6 for my baseline model). It also reports the changes in gender gaps induced by counterfactually closing exogenous gender gaps by ten log points (as in Table 7 for my baseline model). As for the baseline model, I also consider a reference version where the firm-level labor-supply elasticity is considered as exogenous.

Across the different model versions, I find my key results confirmed: First, with endogenous inter-firm mobility, the importance of gender differences in preferences is very limited as substantial shares of gender gaps in labor-market outcomes (e.g., 82-93% of the wage gap) emerge also with preference differences shut off. The importance of preference differences in the importance of non-pay job attributes for the gender gap in inter-firm mobility is only between 15% and 18%. Models that mistake inter-firm mobility as exogenous, by contrast, strongly overestimate the importance of preference differences. The reference models with exogenous mobility, e.g., assign only 49-63% of the gender wage gap to non-preference factors. They particularly overestimate the role of gender differences in the importance of non-pay job attributes to which they assign 37-51% of the gender wage gap and, by construction, 100% of the gender gap in inter-firm mobility. Second, the relation of inter-firm mobility to earnings positions within the household leads to substantial amplification across model versions. Changes in exogenous labor-demand factors (a) or exogenous mobility factors (γ) have effects on the gender wage gap and the gender gap in inter-firm mobility which are 33-59% stronger in the models with endogenous mobility compared to the models with exogenous mobility. There are also moderate effects of changes in exogenous labor-supply factors (ν) on the gender gaps in wage rates and inter-firm mobility which are completely

Table 14: Results of model versions with additional features.

	full model (endogenous mobility)			reference model (exogenous mobility)		
	wage gap	earnings gap	mobility gap	wage gap	earnings gap	mobility gap
Benchmark						
Relative contribution (%) of ...						
... labor-demand gap	85.7	75.4	67.4	57.2	50.3	0
... labor-supply gap	7.1	18.3	16.4	0.0	12.0	0
... non-pay weight gap	7.3	6.4	16.3	42.8	37.7	100
Closure of gap in...						
...labor demand	−15.1	−22.7	−22.7	−10.0	−15.0	0
...labor supply	−1.7	−7.6	−7.6	0.0	−5.0	0
...weight on non-pay	−3.6	−5.4	−15.4	−2.4	−3.6	−10
Model with home production and gender gap in Frisch elasticities						
Relative contribution (%) of ...						
... labor-demand gap	92.6	88.1	78.8	62.4	64.6	0
... labor-supply gap	1.7	6.6	5.9	0.0	5.0	0
... non-pay weight gap	5.6	5.3	15.3	37.6	35.4	100
Closure of gap in...						
...labor demand	−13.4	−21.5	−21.5	−10.0	−16.0	0
...labor supply	−0.4	−2.6	−2.6	0.0	−2.0	0
...weight on non-pay	−2.8	−4.5	−14.5	−2.1	−3.3	−10
Model with firm entry						
Relative contribution (%) of ...						
... labor-demand gap	85.7	75.4	67.4	57.2	50.3	0
... labor-supply gap	7.3	8.5	6.5	0.0	12.0	0
... non-pay weight gap	7.2	6.3	16.2	42.8	37.7	100
Closure of gap in...						
...labor demand	−15.2	−22.8	−22.8	−10.0	−15.0	0
...labor supply	−1.8	−7.7	−7.7	0.0	−5.0	0
...weight on non-pay	−3.5	−5.3	−15.3	−2.4	−3.6	−10
underlineModel with permanent-wage competition						
Relative contribution (%) of ...						
... labor-demand gap	82.7	72.8	65.1	49.0	43.1	0
... labor-supply gap	8.0	19.1	17.1	0.0	12.1	0
... non-pay weight gap	9.4	8.3	18.0	51.0	44.9	100
Closure of gap in...						
...labor demand	−15.8	−23.8	−23.8	−10.0	−15.0	0
...labor supply	−2.0	−7.9	−7.9	0.0	−5.0	0
...weight on non-pay	−4.6	−6.9	−16.9	−2.9	−4.4	−10

Notes: Shares in %. Changes in log points. Models calibrated to married couples. In models with home production and with permanent-wage competition, reference model treats the elasticity of total labor supply to individual firm (including intensive margin) as exogenous.

overlooked by the models which mistake inter-firm mobility as exogenous.