Gender gaps in pay and inter-firm mobility

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Abstract

The gender gap in inter-firm mobility is an important contributor to the gender pay gap but is as yet unexplained. In a structural model of workplace choice, I show that the gender mobility gap can be understood as a consequence of women's typical roles as secondary earners in most households which induces households to put more weight on the non-pay dimensions of women's workplaces. I provide direct empirical evidence for this explanation by documenting that the sensitivity of quits to wages is weaker the less an individual contributes to household earnings. Furthermore, gender differences are small once differences in earner roles are accounted for. My quantitative model evaluations show that ignoring the influence of earner roles on inter-firm mobility leads to substantial biases in wage-gap decompositions and predicted policy effects.

Keywords: Gender gaps, job mobility, discrimination, monopsony

JEL classification: J16, J62, J71, J42

1 Introduction

The gender pay gap is an important issue for society and an interesting phenomenon for economists seeking to understand the functioning of the labor market (e.g., Bertrand et al., 2019, Goldin et al., 2017, Juhn and McCue, 2017). While the gender wage gap has closed substantially over the last 50 years, a substantial gap in wage rates of about 20% still remains in many developed economies. There also is a substantial part of the gender wage gap that cannot be explained by observable characteristics of women and men. Blinder-Oaxaca decompositions of the gender wage gap usually attribute about half of the gender gap to unexplained factors (Blau and Kahn, 2017).

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An important contributor to the unexplained gender wage gap is the gender gap in inter-firm mobility which allows firms to discriminate monopsonistically against women and pay them less than men. It is well documented for the United States (e.g., Ransom and Oaxaca, 2010, Webber, 2016, Mas and Pallais, 2017, Wiswall and Zafar, 2017) and other developed economies (e.g., Barth and Dale-Olsen, 2009, Hirsch et al., 2010, Booth and Katic, 2011, Sulis, 2011, Redmond and McGuinness, 2019) that the workplace choice of women, i.e., for which firm a woman works, is, on average, less sensitive to wage differences between firms than the workplace choice of men. Women's workplace choices, in turn, are more strongly affected by non-pay job characteristics such as collegiality, flexibility, social contribution, or tasks (e.g., 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, 2019, and Redmond and McGuinness, 2020, Gelblum, 2020, Xiao, 2021). Hence, women are less likely attracted to a new firm by better pay and in this sense less mobile between firms. Firms can exploit this lower mobility of women between firms and pay less to women than to men (for evidence, see Ransom and Oaxaca, 2010, and Félix and Portugal, 2017).[1] The potential contribution to the gender wage gap of the gender gap in inter-firm mobility – and the monopsonistic discrimination against women it allows – is quite substantial. In a survey, Hirsch (2016) summarizes the empirical literature by stating that 40-65% of the unexplained gender gap can be attributed to this form of discrimination. Despite its importance, the gender gap in inter-firm mobility is not understood, "evidence on the causes of the gender difference in the wage sensitivity of workers' labor supply to a single employer is still missing" (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 implications for the gender pay gap in a quantitative general-equilibrium model. My explanation for the gender gap in inter-firm mobility is based on a joint decision-making process of households. While the literature has increasingly recognized that labor-supply decisions should be considered as joint decisions of the family (Doepke

[1] In the U.S. and many other developed countries, it is forbidden by law to condition pay on gender. Firms paying less to women nevertheless occurs in various ways. It is documented that women are promoted less frequently (Bosquet et al. 2019; Gobillon et al. 2015; Pekkarinen and Vartiainen 2006; Booth et al. 2003), paid less on a given rank (Blackaby et al. 2005), receive pay raises less often (Babcock and Laschever 2009; Artz et al. 2018), are assigned to lower-paying jobs (Ransom and Oaxaca, 2005) or tasks (Babcock et al., 2017), and are paid less in discretionary compensation components such as bonuses (e.g., Grund, 2015). The gender gap in inter-firm mobility implies that profit-maximizing firms are able to treat women this way without risking the loss of many female workers. Further, the gender gap in inter-firm mobility implies that women leave low-pay firms at lower rates than men such that in the long run men work at better paying firms (Card et al. 2018; Bayard et al. 2003).

and Tertilt 2016), most papers focus on the choice of whether or how much to work.[2] I expand this notion to the choice of where to work and whether to change jobs.[3] I focus on the weighing of pay and non-pay characteristics of different jobs when choosing between them and, in my model, spouses decide jointly how much weight to put on these two dimensions.

I argue that pay is a less important determinant of the choice of women's workplaces not primarily because women care intrinsically more about non-pay characteristics of a job but because the household does not rely so much on their earnings. Consider a dual-earner household where income potentials of the spouses differ, for example because they differ in labor-market experience which is valued by firms. In such a situation, a certain percentage increase in income matters particularly when it concerns the spouse with the higher earnings potential. In turn, this makes non-pay characteristics more important relative to pay when deciding about where the other spouse should work. I formalize these relations in a model of workers' choices between heterogeneous workplaces that is similar to the models considered by Card et al. (2018) and Wiswall and Zafar (2017) and extends them by introducing dual-earner couples. I derive the wage sensitivity of a worker's employer choice as a function of the share that this worker contributes to household earnings. This way, one can interpret the gender gap in inter-firm mobility as reflecting the mobility difference between individuals with different earner roles in the household. This is due to the fact that, statistically, women are contributing lower average shares to household earnings than men.[4]

[2] 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 understand 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).

[3] 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 likeable job characteristics for husband and wife.

[4] In line with my explanation based on within-household earner roles, 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 expected to be rather constant across the population and over time.

As a testable prediction, my model implies that the wage sensitivity of quits is stronger for people who contribute larger shares to household earnings. I test this prediction in quit regressions where I include the share of contributed earnings and interact it with the wage rate. The empirical results are strongly supportive of my theory. I find a significant, quantitatively important, and robust effect of intra-household earner roles on the wage sensitivity of quits in the expected direction. My empirical results imply that an increase of an individual's contributed share to household earnings by ten percentage points raises the individual's mobility between firms by about 10 percent. Once I take earner roles into account, the 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 equal shares to household earnings.

Regarding the consequences for the gender wage gap, my results imply a mutually enforcing cycle between gender gaps in pay and inter-firm mobility. For example, if an experience gap between men and women makes firms willing to pay higher wage rates to men than to women, this initial wage gap is amplified because households will respond to it by supplying female labor less elastically to individual firms which in turn allows firms to reduce women's wages further. Similar mechanisms amplify initial gender differences in labor supply or non-pay job preferences. I provide a quantitative model assessment that shows that the cycle 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%.

As a consequence of this amplification, a model that takes into account this feedback between the gender gap needs smaller exogenous differences between men and women in order to generate gender gaps in outcomes and explains larger fractions of these gender gaps endogenously through economic mechanisms. By contrast, models that mistake inter-firm mobility and gender differences therein as exogenous yield biased estimates concerning the importance of different contributors to wage gaps. My quantitative analysis indicates that taking into account the effect of household earner roles for inter-firm mobility reduces the gender differences in non-pay job preferences required to match observed gender gaps by a factor of about 5 and increases the share of the gender wage gap that should be assigned to labor-demand factors such as experience by about one third.

The amplification mechanism proposed in this paper stands complementary on other recently developed mechanisms that show that household decisions can amplify differences between men and women. Flabbi and Mabli (2018) show that the gender gap in accepted wages can exceed the gap in wage offers considerably because couple households may accept low job offers for women in order to be able to afford searching for high wage jobs for men.[5] Location choices of dual-earner couples amplify pay differences between members when they are determined primarily by the household's aim to foster the primary earner's career (Averkamp et al., 2021) and improving earnings opportunities for women reduce the number of male-driven household moves (Braun et al., 2021), thereby amplifying the effect on the wage gap.

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 to demonstrate the basic mechanism behind my results. To keep the basic model as simple and transparent as possible, I start with a static set-up that includes only the monopsonistic friction like the ones used by Card et al. (2018) and Wiswall and Zafar (2017) to which I add dual-earner couples. A dynamic monopsony representation that delivers identical steady-state results can be found in Appendix A.1. I address search costs in Appendix A.3. Several additional features (such as endogenous hours choices, segregated labor markets, within-gender inequality, singles, gender differences in elasticities of labor supply to the market, home production, and firm entry) which are abstracted from in the basic model I will address in the quantitative model analysis in Section 4.

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 take workplace choices jointly. Firms differ in non-pay characteristics (such as location, the tasks to be performed, the work climate, the flexibility or predictability of a job) over which workers have heterogeneous

[5] 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 reservations wages of the partner of highly educated individuals are compressed through increased willingness to bear risk and the partner's comparative advantage in search. Through these channels, family decisions tend to reduce pay differences between spouses.

preferences.[6] This gives firms local monopsony power over the workers who like the respective firm's 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 costlessly observe. Based on these wage rates, households choose a firm for each worker and firms hire any worker who is willing to accept a job at 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. To clarify, 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 but not an all-encompassing theory explaining the deep roots of those differences. My model still needs a trigger which sets in motion the amplifying mechanisms I highlight. Yet, it is a key implication of the model that very small amounts of these triggers can be sufficient 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 for both spouses in order to maximize

$$u = \ln c + \frac{1}{\gamma_f} \cdot \varepsilon_f\left(k_f\right) + \frac{1}{\gamma_m} \cdot \varepsilon_m\left(k_m\right), \tag{1}$$

where the $\varepsilon_g\left(k_g\right)$, with $g = f, m$ indexing gender, describe utility from non-pay characteristics of the chosen firm.[7] I assume that the additional utility agents achieve at the different potential employers, $\varepsilon_g(v)$, 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.[8] I allow these weights to be gender-specific but

[6] 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) have shown empirically that such non-pay characteristics play a major role for workers' job search behavior.

[7] I abstract from complementarities between the non-pay characteristics of spouses' jobs in utility. An easy way to introduce such complementarities were to let the weight γ_g depend on the 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 makes strategic interaction negligible but also implies that the share of such couples is minimal.

[8] I scale the distribution of taste shifters ε 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

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.

Households act subject to the budget constraint

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

where $w_g\left(k_g\right)$ 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.

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

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

where $-g$ denotes the other gender. Consequently, the total mass of workers of gender g working for firm j is[9]

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

As Card et al. (2018), I assume that strategic interaction between firms in wage setting is negligible and consider a symmetric equilibrium.[10] This implies that the slope of the labor-supply curve faced by an individual firm is

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

innocuous in the basic model considered here but affects the interpretation of the quantitative model (see Section 4) where I consider different labor-market segments which differ in V, and matters in an extension where I consider firm entry which makes V endogenous.

[9] 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.

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

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.[11]

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 how many firms there are because the number of firms V determines how similar each firm is to the most similar firm 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 very 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

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

The mobility gap hence depends on gender differences in the intrinsic importance of job characteristics and the gender gaps in hourly wage rates and hours worked. It thus reflects both, gender differences in, say, psychological aspects determining the importance of job characteristics and endogenous differences stemming from roles in the household. An example for the former can be gender differences in risk aversion (e.g., Croson and Gneezy, 2009, Iriberri and Rey Biel, 2019) which can lead women to dislike uncertain work environments more strongly than men (Heinz et al. 2016).[12] 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 unlikeable 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

[11] Appendix A.2 presents an alternative derivation of the elasticity of labor supply to individual firms that focuses on worker's quit decisions in response to wage cuts by their employers. In 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.

[12] Alternative examples include differences in self-confidence (Bordalo et al. 2019), the attraction to high stakes (Azmat et al. 2016), bargaining (Hernandez-Arenaz and Iriberri 2018), or self-promotion (Exley and Kessler 2021).

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 $V = 10$.

gender differences in inter-firm mobility are driven rather by the latter than the former aspect.[13]

Figure 1 illustrates the elasticity of labor supply to individual firms as a function of the husband's contributed share to household earnings. For the figure, I assume that there are no 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 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 than the secondary earner. 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

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

where a_g is the marginal revenue product of workers of gender g, subject to the labor-supply schedule they face from workers of both genders (described by (3) for $g = f, m$).

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

As is well known in models of monopsonistic labor markets, it is profit-maximizing for firms to offer a given group 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

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

It follows that 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 elasticity of labor supply to individual firms and which 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.[14]

2.3 Equilibrium gender gaps

Equilibrium gender gaps solve the system of equations (5) and (7) and are given by

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

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 neatly illustrate the mutually enforcing cycle 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 gender earnings gap, see (9).

[14] Note that a gender gap in marginal revenue products, Δa, does not necessarily mean that women per se are worse in performing certain tasks. It 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 interpretation of Δa in mind, I will refer to it as the gender gap in labor-demand factors.

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

$$u_g = \ln c_g + \frac{1}{\gamma_g} \cdot \varepsilon_g \left(k_g\right)$$

subject to

$$c_g = w_g \left(k_g\right) h_g.$$

It is straightforward to show that

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

in this model version.

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 given by

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

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

in this version. 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 gap in inter-firm mobility. 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 which facilitates understanding the respective 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 mutually enforcing cycle 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 but, through this, 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 below marginal revenue product and thus exerts a second, indirect effect on the wage gap. This then again affects the mobility gap and so on.[15] A model that overloooks 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 to reduce the amount of gender differences in preferences required to rationalize observed gender gaps. Formally, the two competing model versions match given observations Δw and $\Delta\eta$ for the exogenous gender gaps given in the middle block of Table 1. While the calibrated 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 with couples generates a gender gap in inter-firm mobility 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 calibration results 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

[15] Similarly, a reduction in the importance of non-pay characteristics of women's workplaces makes women 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.

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, $\Delta w\vert_{\Delta a}/\Delta w$	$\frac{\eta+1}{\eta} \cdot \frac{\Delta w - \frac{1}{1+\eta}\Delta\eta}{\Delta\eta}$	$\frac{\Delta w - \frac{1}{1+\eta}\Delta\eta}{\Delta\eta}$
... preference differences, $\Delta w\vert_{\Delta\gamma}/\Delta w$	$\frac{1}{1+\eta} \cdot \frac{\Delta\eta - \Delta w - \Delta h}{\Delta w}$	$\frac{1}{1+\eta} \cdot \frac{\Delta\eta}{\Delta w}$
... labor-supply differences, $\Delta w\vert_{\Delta h}/\Delta w$	$\frac{1}{\eta} \cdot \frac{\Delta h}{\Delta w}$	0
Share of mobility gap explained by...		
... labor-demand differences, $\Delta\eta\vert_{\Delta a}/\Delta\eta$	$\frac{\eta+1}{\eta} \cdot \frac{\Delta w - \frac{1}{1+\eta}\Delta\eta}{\Delta\eta}$	0
... preference differences, $\Delta\eta\vert_{\Delta\gamma}/\Delta\eta$	$\frac{\Delta\eta - \Delta w - \Delta h}{\Delta\eta}$	1
... labor-supply differences, $\Delta\eta\vert_{\Delta h}/\Delta\eta$	$\frac{\eta+1}{\eta} \cdot \frac{\Delta h}{\Delta\eta}$	0

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.[16] Put 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.[17]

Additionally, my model analysis suggests an additional driver of pay differences between men

[16] 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 $(\eta+1)/\eta > 1$. $\Delta w|_{\Delta\gamma}/\Delta w$ 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 $\Delta w + \Delta h > 0$.

[17] 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 between men and women due to the amplifying cycle between the gender gaps in pay and inter-firm mobility discussed above.

and women. Unlike the reference model, the full model has a role of labor-supply differences between men and women for the gender wage gap. When women supply less labor than men, their earnings are less important to households than men's, setting in motion the mutually enforcing cycle discussed before. Hence, in my model, 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. A model that neglects the endogeneity of inter-firm mobility which arises from joint decision making of dual-earner households overlooks this channel.

2.6 A 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 Appendix A.4, I outline an extended model that features worker flows between firms resulting from idiosyncratic shocks to workers' preferences over different firms and pay differences between firm resulting from permanent firm-specific productivity shocks. While both extensions have no impact on the results obtained so far, they allow to calculate the fraction of workers in group g quitting their jobs at firm j in any given period as

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

where θ is the fraction of workers drawn to receive new job-specific preferences and w_g is the average wage rate paid to workers of group g. The term $1/V \cdot (1 + \eta_g \ln(w_{g,j}/w_g))$ describes the fraction of workers whose preferences over firms have changed but still continue to work on their existing jobs, i.e., do not quit. This fraction is higher when the firm pays higher wages and the sensitivity depends on the elasticity η_g derived before. Importantly, my theory predicts η to depend 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

$$q_i = \beta_0 + \beta_1 \cdot \ln w_i + \beta_2 \cdot e_i \cdot \ln w_i + \beta_3 \cdot e_i + \gamma \cdot \widetilde{w}_{i,g} + \zeta_i, \tag{14}$$

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, $\widetilde{w}_{i,g}$ describes the overall (average) pay to workers like worker i (standing for wage offers from alternative employers), and ζ_i is a residual.

The main testable prediction of my theory is that regression (14) yields a negative coefficient on the interaction term,

$$\widehat{\beta}_2 = -\theta\gamma_i < 0. \tag{15}$$

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. This information is crucial for my purposes since I analyze the impact of household earner roles on worker mobility. 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.[18]

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-

[18] 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. (2021) 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, by construction, has no information on firms' hiring behavior because the unit of observation in the data set is a household, not a firm. By contrast, firm 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.

firm separations for both genders continuously from 1979 (hence jobs held in 1978) on. For full transparency, Appendices B.2, B.1, and B.3 provide detailed descriptions of the sample selection, the definition of variables, and the specification of the different regressions.

As my baseline regression, I estimate

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

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 $\ln w_{ijt} \cdot e_{it}$ could pick up trends in the wage sensitivity of quits rather than the influence of earner roles within the worker's household.[19] 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 year, education, the number of children, region, and race.[20]

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. Apart from the reduced generality, such an approach is impossible in my data because the respondent's employer is unknown.

I also run specifications where I instrument the earnings contribution e_{it} and account for the potential role of parenthood. In robustness checks, I estimate non-linear (probit and logit) models,

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

[20] 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.

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.

First, I consider a specification without 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 Oaxaca (2010) and Hirsch et al. (2010).

Columns (3) and (4) report results for my baseline specification including the interaction of wages and the contributed earnings share. 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 linear effect of the (non-interacted) log wage rate is now very similar across genders. Once different earner roles are accounted for, there remain little gender differences in inter-firm mobility. 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, not per se but because of their earner roles within the household.

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. 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 quitting behavior is substantially less sensitive to wages with numbers being comparable to the

Table 2: The wage sensitivity of quits.

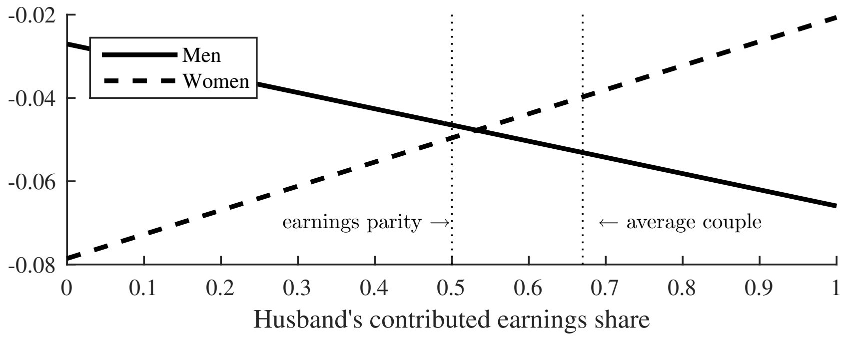
	(1) men	**(2) women**	**(3) men**	**(4) women**
log wage rate	-0.0488^{***}	-0.0294^{**}	-0.0465^{***}	-0.0469^{***}
	(0.0158)	(0.0164)	(0.0158)	(0.0171)
log wage rate			-0.0389^{***}	-0.0579^{***}
$\times$ (earnings share-0.5)			(0.0130)	(0.0162)
observations	20231	20131	20231	20131
marginal effect of $\ln w$...				
... 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, $\ln w \times t$, $\ln w \times t^2$. Variable definitions, sample selection, and specification described in detail in Appendices B.1, B.2, and B.3, respectively.

linear effect in columns (1) and (2). By contrast, the empirical model predicts that, if husbands and wives contributed equal shares to household earnings, they would also show a similar mobility between firms: at an earnings contribution of 0.5 ("earnings parity"), gender differences in the marginal effect of the wage rate on the quit probability are small.

Table 3 contains results of additional estimations. 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 partner's industry and partner's occupation. When I follow this strategy, I find my main results confirmed, see first row

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



Notes: Marginal effect of $\ln w$.

in Table 3. The 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 for which results are shown in the second and third rows of Table 3. 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. 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.[21]

May baseline regressions include quits into out of labor force but such quits do not occur in

[21] 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 the choice of fathers' workplaces more wage-sensitive and the choice of mothers' workplaces less wage-sensitive. 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 that consists mostly of relatively young or relatively old workers.

Table 3: Accounting for the potential endogeneity of the earnings contribution, the role of children, and transitions out of labor force.

		men	**women**
i.	IV	-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, $t \times \ln w$, Xe. Variable definitions, sample selection, and specification described in detail in Appendices B.1, B.2, and B.3, respectively.

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 my results indeed reflect the quitting behavior of workers transitioning to a new job directly or shortly after.

To check robustness, 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 since 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 determinants X with the earnings contribution.

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 $\ln w$	-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, $t \times \ln w$, Xe. Variable definitions, sample selection, and specification described in detail in Appendices B.1, B.2, and B.3, respectively.

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. 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 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

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, $t \times \ln w$. Variable definitions, sample selection, and specification described in detail in Appendices B.1, B.2, and B.3, respectively.

the results. In line with the theory, 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.[22] 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-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

I now quantify my theoretical results regarding the feedback mechanism between gender gaps in pay and inter-firm mobility. To this end, I extend my model to take into account further aspects

[22] 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.

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. I also address a number of 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) in additional model versions considered in the Appendix. I calibrate the model and use it for counterfactual experiments such as gender-gap decompositions and comparative statics.

4.1 Additional model features

Vertical and horizontal segregation. Segregation of men and women into different segments of the labor market is an important aspect of the gender wage gap (see, e.g., Blau and Kahn, 2017). Further, this segregation is affected by similar mechanisms as the one regarding workplace choices described in my basic model. E.g., when workers decide in which industry to work, a similar weighing between pay and non-pay characteristics of the industry takes place and, when this is done in the family, the weight that is put on the two dimensions is affected by similar considerations as firm choices considered in the basic model from Section 2.

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 contribution to firms' marginal revenue product. As an example, an individual's horizontal choice could be to concern herself with law rather than finance or medicine. Her vertical choice could be to be a lawyer rather than a paralegal or to invest into becoming a partner rather than remaining at lower levels of the hierarchy. The decision which law firm to work for would be the choice of workplace already considered in the basic model in Section 2.[23]

Formally, (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

[23] While these decisions are in parts taken before couple households form, there is empirical evidence that single women anticipate their future role in marriages when making career choices (Bursztyn et al. 2017).

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.

Heterogeneity in horizontal and vertical labor-supply choices is achieved through two modelling elements. First, individuals have preferences over the different segments of the labor market like they have preferences over workplaces within these segments. These preferences are also a stand-in for the costs of education as far as they affect which labor-market segment is or can be entered. Specifically, 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 σ. Second, I allow for within-gender (and within-education) heterogeneity in productivity which affects a worker's marginal revenue product in a firm, 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 $\alpha_z \cdot a_i$.

Endogenous hours choice. While hours worked are exogenous in the basic model, I now incorporate 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.

Formally, instead of (1), household preferences are now described by

$$\begin{aligned} u = &\ln c - \frac{1}{\nu_f} \cdot \frac{h_f^{1+1/\psi}}{1+1/\psi} - \frac{1}{\nu_m} \cdot \frac{h_m^{1+1/\psi}}{1+1/\psi} \\ &+ \frac{1}{\gamma_f} \cdot \varepsilon_f\left(k_f\right) + \frac{1}{\gamma_m} \cdot \varepsilon_m\left(k_m\right) + \frac{1}{\gamma_f} \cdot \epsilon_f(y_f, z_f) + \frac{1}{\gamma_m} \cdot \epsilon_f(y_m, z_m), \end{aligned} \tag{16}$$

which also includes the direct utility workers achieve from their horizontal and vertical labor-market choices, ϵ_g. In (16), 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.[24] Gender differences in ν, $\Delta\nu = \ln \nu_m - \ln \nu_f \neq 0$, measure

[24] I allow for gender differences in the Frisch elasticity in Appendix C.4

differences in households willingness to supply the labor of men and women. This willingness can depend on the bargaining power of the spouses, their preferences, their productivity in non-market work, and also on social norms regarding gender roles.

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.[25] 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 $U = u + \beta U'$.

Singles. 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, 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

$$u_g = \ln c_g - \frac{2}{\nu_g} \cdot \frac{h_g^{1+1/\psi}}{1+1/\psi} + \frac{2}{\gamma_g} \cdot \varepsilon_g(k_g) + \frac{2}{\gamma_g} \cdot \epsilon_g(y_g, z_g) \tag{17}$$

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 (16). This does not affect consumption, which is household-public.

Appendix C.1 discusses some technical assumptions and presents a formal summary of the equilibrium conditions of the quantitative model.

[25] In Appendix C.4, I also consider the case of competition in permanent wages which delivers similar results.

4.2 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 6. 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).[26] 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%.[27] 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).[28]

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 $\gamma_m = 0.441$.

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

[26] 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.

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

[28] I vary the parameters of the process for firm-specific productivity in Appendix C.2.

Table 6: 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: $\Delta x = \ln x_m - \ln x_m$. lp = log points.

two thirds and four thirds which mimics a college to no-college wage ratio of 2 while pertaining an average value of one.[29] 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.[30] I set the variance of the taste shifters to 0.52 to match

[29] 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).

[30] 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).

Table 7: 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.

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.[31]

4.3 Status-quo analysis

The model does not need large exogenous differences between genders, see the bottom block of Table 6. 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. The gender gap in the preference weight on labor supply which influences the gender gap in hours worked is only about 10% while men work 14% longer hours than do women. Most importantly, I need to put into the model only very little 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.

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

Table 7 considers non-targeted moments. 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 7. 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 7. The good model performance with respect to non-targeted moments provides confidence that the calibrated model is a suitable laboratory for counterfactual analysis.

As a final status-quo analysis, I perform quit regressions like the one considered in the empirical analysis. Specifically, I simulate the model around its steady state, generate artificial data which I then use to perform the same estimations as in Table 2. The aim of this exercise is twofold. First, I want to make sure that the model features relations between quits and wages that are in line with their empirical counterparts because this relation is the moment that identifies gender differences in the elasticity of labor supply in many empirical studies. Second, I want to corroborate the ability of my extended quit regressions to differentiate differences in household earner roles from gender differences in the importance of non-pay job characteristics in utility.

I describe the simulation and estimation in detail in Appendix C.2 and concentrate on the results here. Table 8 shows mean results from 10,000 Monte-Carlo estimations from the simulated data. 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 8 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.2,

Table 8: 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.

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.

4.4 Counterfactual analysis

I perform two series of counterfactuals which aim at determining the importance of the different gender gaps in exogenous factors to the endogenous gender gaps in labor-market outcomes and at quantifying the degree of amplification due to the feedback mechanism between the gender gaps.

Decomposition. To decompose the gender gap in labor-market outcomes into the consequence of the three exogenous gender differences that the model knows, I perform counterfactual model evaluations where I shut of gender differences by setting the respective parameter for women to its value for men. Specifically, I first shut off gender differences in the disutility of work, i.e., set $\Delta\nu$ to zero. Second, I shut off gender differences in the utility weights on non-pay job attributes, i.e., set $\Delta\gamma$ to zero. Third, I shut off all gender differences in preferences, i.e., set both $\Delta\nu$ and $\Delta\gamma$ to zero. I do this for my full model and for a reference model in which I shut off my mechanism and treat inter-firm mobility as exogenous, i.e., a model version where η is a parameter.[32]

The results are shown in the upper block of Table 9 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

[32] To focus on inter-firm mobility, I continue to model the choices of labor-market segments as a joint decision of couples.

Table 9: Shutting off gender differences in preferences.

	full model (endogenous mobility)			**reference model** (exogenous mobility)		
	Δw	Δwh	$\Delta\eta$	Δw	Δwh	$\Delta\eta$
A) Full calibration	19.9 lp	32.6 lp	29.7 lp	19.9 lp	32.6 lp	29.7 lp
B) $\Delta\nu = 0$	18.6 lp	26.3 lp	25.7 lp	19.5 lp	26.9 lp	29.7 lp
C) $\Delta\gamma = 0$	17.8 lp	29.9 lp	22.1 lp	12.6 lp	22.9 lp	0.0 lp
D) $\Delta\nu = 0$ and $\Delta\gamma = 0$	16.6 lp	23.6 lp	17.2 lp	12.3 lp	17.2 lp	0.0 lp
Relative contribution of ...						
... $\Delta\bar{a}$ $(= D/A)$	83.8%	72.4%	57.9%	62.1%	52.8%	0.0%
... $\Delta\gamma$ $(= (B-D)/A)$	10.1%	8.3%	28.6%	36.4%	29.8%	100.0%
... $\Delta\nu$ $(= (C-D)/A)$	6.1%	19.3%	13.1%	1.5%	17.5%	0.0%

Notes: $\Delta x = \ln x_m - \ln x_m$. $\Delta x = 0$ means x_f is set to x_m. lp = log points. Levels of wage rates, hours, and elasticities of labor supply to individual firms shown in Table 13 in Appendix C.3.

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 9 shows the percentage contributions of the different exogenous gender gaps on the endogenous gaps, as implied by the counterfactual evaluations.

The results show that 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, i.e., with gender differences only in labor-demand factors, captured in the model through differences in marginal revenue products, the model still generates almost 85% of the gender wage gap, almost 75% of the gender gap in earnings, and more than 60% 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 gender gaps in labor-market 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.[33] 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 hugely overestimates the causal role of gender differences in preferences over jobs.

[33] 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.

As discussed in Section 2, my model suggests that gender differences in labor-supply factors have an influence on how mobile men and women are between firms and how strongly firms can discriminate monopsonistically against women. The quantitative results in Table 9 show that this effect is not negligible as about 6% of the gender wage gap is assigned to gender differences in labor-supply factors. This effect is overlooked by a model where inter-firm mobility is considered as exogenous. In the reference model, labor-supply factors only exert a small effect on gender-specific wages through composition effects that reflect the segregation across labor-market segments.

Amplification. I now vary parameters in order to assess the quantitative degree of amplification due to endogenous inter-firm mobility. Specifically, I close one of the gender gaps in exogenous parameters in each experiment. Put differently, I make men and women more similar in the respective dimension. The results are shown in Table 10. The numbers give the gender gaps in wage rates, earnings, and inter-firm mobility for the baseline calibration and the different counterfactuals (in log points). Numbers in brackets give the absolute change (in log points) in the respective gap relative to the baseline calibration with all three exogenous gender gaps shut on. As in Table 9, 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 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, the effects are amplified through the mutually enforcing cycle between gender gaps in pay and inter-firm mobility. The cycle amplifies the effect on the gender wage gap 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.

Table 10: Closing exogenous gender gaps.

	full model (endogenous mobility)			reference model (exogenous mobility)		
	Δw	Δwh	$\Delta \eta$	Δw	Δwh	$\Delta \eta$
baseline calibration	19.9 lp	32.6 lp	29.7 lp	19.9 lp	32.6 lp	29.7 lp
change in demand $\Delta a \downarrow 10\,\mathrm{lp}$	6.0 lp (-13.9 lp)	13.5 lp (-19.1 lp)	17.6 lp (-12.1 lp)	9.0 lp (-10.8 lp)	18.1 lp (-14.5 lp)	29.7 lp (±0.0 lp)
change in supply $\Delta \nu \downarrow 10\,\mathrm{lp}$	18.6 lp (-1.3 lp)	26.2 lp (-6.4 lp)	25.7 lp (-4.0 lp)	19.6 lp (-0.2 lp)	27.8 lp (-4.8 lp)	29.7 lp (±0.0)
change in mobility $\Delta \gamma \downarrow 10\,\mathrm{lp}$	16.6 lp (-3.2 lp)	28.2 lp (-4.4 lp)	15.8 lp (-13.9 lp)	17.3 lp (-2.5 lp)	29.2 lp (-3.4 lp)	19.7 lp (-10.0 lp)

Notes: Closures of exogenous gaps achieved through changing female parameter accordingly. $\Delta x = \ln x_m - \ln x_f$. lp = log points. Levels of wage rates, hours, and elasticities of labor supply to individual firms shown in Table 13 in Appendix C.3.

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 which raises 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 mutually reinforcing cycle 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 change in $\Delta \bar{a}$ 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 $\Delta \nu$ can be thought of as anything that pushes the relative labor-supply curves, hence 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 $\Delta \gamma$ 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 mark-downs 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 household earner roles 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 couple also constitute promising avenues for future research.

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Appendix to "Gender Gaps in Pay and Inter-firm Mobility"

A Additional analytical results

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). Inflow and outflow rates of workers of group g, i.e. quit rates and the number of recruits, depend on wage rates offered by the firm to workers of this group and are denoted by $q_g\left(w_g\right)$ and $r_g\left(w_g\right)$, 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

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

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

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

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

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

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 the elasticity of labor supply to individual firms

In this appendix, I derive the elasticity of labor supply to individual firms in a way that puts worker flows between firms and, in particular, workers' quit decisions into the center of the analysis. For this, I slightly change the way I model 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 elasticity of labor supply to individual firms as does the baseline model presented in Section 2.

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 $v = 0,\ ^1/_V,\ ^2/_V,\ ...,\ 1$. 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. In particular, the household target function is

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

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 workers who work for a given firm and evaluate how many of these workers would decide not to work for this firm if the firm were to change its wage offer by factor z. Each individual worker bases his or her decision whether to continue to work for this firm or whether to switch firms on a comparison of the costs of staying with the firm and the costs Γ_g of switching to another firm,

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

The left-hand side of the condition above describes the costs of staying with the firm and the right-hand side the costs of switching employers. 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

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

where $\bar{n}_g$ is the comparison employment level without the pay cut and $\text{cdf}_{\Gamma,g}$ 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

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

where $\text{pdf}_{\Gamma,g}$ is the probability 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 the fact that marginal utility λ equals c^{-1} with log utility gives the elasticity of labor supply to individual firms 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 model presented in 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 reality, there are of course also monetary costs of quitting an employer, importantly search costs. After reentering employment, there are also earnings penalties for having been unemployed which increase in the length of the past unemployment spell. It is potentially important to consider these dimensions as women on average remain longer in unemployment than men. 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 because, also here, I will focus on the quit decision of a worker.

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 now $q = \text{cdf}_{\Gamma+\Omega}(z \cdot wh \cdot \lambda)$ and the elasticity of labor supply to individual firms is

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

Two things 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 elasticity of labor supply to individual firms 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, $\Delta\gamma = \ln\gamma_m - \ln\gamma_f$ 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 Deriving a testable prediction

In order to perform quit regressions in my model, I need to incorporate worker flows between firms and wage differences across firms and, to this end, I add two elements to the model, both of which do not alter the results obtained so far. 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. 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. To induce wage differences across firms, I assume that firms face small idiosyncratic permanent productivity shocks. 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.[34]

In this simple environment, 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 times the fraction of those workers who afterwards prefer to work for a different firm, by

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

where w_g is the average wage rate paid to workers of group g and the last step uses a first-order Taylor approximation in logs. Using a first-order Taylor approximation in logs, this expression can be rearranged to equation (13) in the main text.

[34] 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 $\ln a_{g,j,t} = (1-\rho)\ln a_g + \rho \ln a_{g,j,t-1} + \xi_{j,t}$, 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 following 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 industry 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 completed 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 11 summarizes some descriptive statistics about the final sample.

Table 11: 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.

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 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, age dummies, 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 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 likeable 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.4

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 partner's productivity $-x$, partner's vertical position $-y$, and partner's horizontal position $-z$, the following conditions describe the steady state,

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

$$\phi_p = \gamma_g \cdot V_z \cdot w_p h_p / (w_p h_p + w_{-p} h_{-p}) + \psi, \tag{C.2}$$

$$h_p^{1/\psi} = \nu_g \cdot c_p^{-1} \cdot w_p, \tag{C.3}$$

$$c_p = w_p h_p + w_{-p} h_{-p}, \tag{C.4}$$

where $-p = \{-g, -x, -y, -z, x, y, z\}$ describes the partner's cell. Conditions (C.1) to (C.4) 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 (16)) 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 (17)) net of taste shifters and N is the set of feasible choices for the group.[35] 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.

C.2 Quit regressions in the model

While all other model evaluations only consider steady states, the quit regressions presented in Table 8 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 4.1. 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

[35] 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.

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 Monte-Carlo style exercise. For my baseline calibration, the results are shown in Table 8 in the main text.

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. (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.

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.

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.3 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 9 and 10.

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.4 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 4.2, 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.[36] 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.

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.1) to (C.4) 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

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

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 dif-

[36] 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 $\eta_f = 1.6402$.

ferences 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.[37] 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. (2019).[38]

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,

$$(a_m - w_m)h_m/V - (a_f - w_f)h_f/V - \kappa = 0. \tag{C.5}$$

Note that V impacts on both wage rates and hours. Technically, V becomes an additional endogenous variable and (C.5) 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 4.2.

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

[37] 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.

[38] 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.

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.2). The uncompensated elasticity is endogenously gender-specific and reads

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

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 9 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 10 for my baseline model). As for the baseline model, I also consider a reference version where the elasticity of labor supply to individual firms 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

Table 14: Results of model versions with additional features.

	full model (endogenous mobility)			**reference model** (exogenous mobility)		
	Δw	Δwh	$\Delta\eta$	Δw	Δwh	$\Delta\eta$
Benchmark						
share of gap created…						
…without preference gaps	85.7%	75.4%	67.4%	57.2%	50.3%	0.0%
…by $\Delta\nu$	7.1%	18.3%	16.4%	0.0%	12.0%	0.0%
…by $\Delta\gamma$	7.3%	6.4%	16.3%	42.8%	37.7%	100.0%
change in gap induced by …						
…10 lp reduction in Δa	−15.1 lp	−22.7 lp	−22.7 lp	−10.0 lp	−15.0 lp	0.0 lp
…10 lp reduction in $\Delta\nu$	−1.7 lp	−7.6 lp	−7.6 lp	0.0 lp	−5.0 lp	0.0 lp
…10 lp reduction in $\Delta\gamma$	−3.6 lp	−5.4 lp	−15.4 lp	−2.4 lp	−3.6 lp	−10.0 lp
Model with home production and gender gap in Frisch elasticities						
share of gap created …						
…without preference gaps	92.6%	88.1%	78.8%	62.4%	64.6%	0.0%
…by $\Delta\nu$	1.7%	6.6%	5.9%	0.0%	5.0%	0.0%
…by $\Delta\gamma$	5.6%	5.3%	15.3%	37.6%	35.4%	100.0%
change in gap induced by …						
…reduction in Δa	−13.4 lp	−21.5 lp	−21.5 lp	−10.0 lp	−16.0 lp	0.0 lp
…reduction in $\Delta\nu$	−0.4 lp	−2.6 lp	−2.6 lp	0.0 lp	−2.0 lp	0.0 lp
…reduction in $\Delta\gamma$	−2.8 lp	−4.5 lp	−14.5 lp	−2.1 lp	−3.3 lp	−10.0 lp
Model with firm entry						
share of gap created …						
…without preference gaps	85.7%	75.4%	67.4%	57.2%	50.3%	0.0%
…by $\Delta\nu$	7.3%	8.5%	6.5%	0.0%	12.0%	0.0%
…by $\Delta\gamma$	7.2%	6.3%	16.2%	42.8%	37.7%	100.0%
change in gap induced by …						
…10 lp reduction in Δa	−15.2 lp	−22.8 lp	−22.8 lp	−10.0 lp	−15.0 lp	0.0 lp
…10 lp reduction in $\Delta\nu$	−1.8 lp	−7.7 lp	−7.7 lp	0.0 lp	−5.0 lp	0.0 lp
…10 lp reduction in $\Delta\gamma$	−3.5 lp	−5.3 lp	−15.3 lp	−2.4 lp	−3.6 lp	−10.0 lp
Model with permanent-wage competition						
share of gap created …						
…without preference gaps	82.7%	72.8%	65.1%	49.0%	43.1%	0.0%
…by $\Delta\nu$	8.0%	19.1%	17.1%	0.0%	12.1%	0.0%
…by $\Delta\gamma$	9.4%	8.3%	18.0%	51.0%	44.9%	100.0%
change in gap induced by …						
…10 lp reduction in Δa	−15.8 lp	−23.8 lp	−23.8 lp	−10.0 lp	−15.0 lp	0.0 lp
…10 lp reduction in $\Delta\nu$	−2.0 lp	−7.9 lp	−7.9 lp	0.0 lp	−5.0 lp	0.0 lp
…10 lp reduction in $\Delta\gamma$	−4.6 lp	−6.9 lp	−16.9 lp	−2.9 lp	−4.4 lp	−10.0 lp

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

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