Home Bias and the Gender Wage Gap

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PRELIMINARY AND INCOMPLETE

June 20, 2023

Abstract

This paper examines the relationship between home bias in location decisions and the gender wage gap. We explore the notion that women's stronger attachment to their home locations can contribute to the gender wage gap. There are two main channels: sorting and labor market power. Women's stronger attachment to their home locations hinders efficient sorting into occupations and locations, contributing to a gender wage gap in equilibrium. Moreover, firms exploit women's relative lower spatial mobility, exerting greater labor market power and widening the wage gap. We develop a model that captures these two channels. A numerical illustration shows that the inclusion of the labor market power channel magnifies the gender wage gap.

1 Introduction

There is evidence that women prefer shorter distances in their everyday commute to work (Gutiérrez and Philippon, 2016; Le Barbanchon, Rathelot, and Roulet, 2021). Thus, women limit their search span and self-select into jobs closer to their home. This partially contributes to the gender wage gap as women do not pursue their comparative advantage, with respect to income, as strongly as men do. Other literature has highlighted the role of an individual's home location to explain location decisions within a country (Kennan and Walker, 2011; Diamond, 2016; Heise and Porzio, 2019; Zerecero, 2021). In other words, there is a home bias in individual's location decisions. So, differences in home bias between men and women can also contribute to the gender wage gap. This paper aims to understand and quantify the role of home bias in the gender wage gap, as well as their broader implications in the economy.

Differences in home bias can affect the gender wage gap through two main channels: first, similar to the shorter-commuting mechanism highlighted by Le Barbanchon et al. (2021), women's tendency to limit their location choices to be closer to their homes results in suboptimal sorting into jobs compared to men. Second, firms may exert more monopsony power over native women if their labor market and migration decisions are less responsive to wage changes compared to men. This differential labor market power across men and women exacerbates the gender wage gap in equilibrium. Therefore, disparities in home bias between genders can help explain variations in geographical labor supply elasticities, as first proposed by Madden (1977). This second channel

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may be especially relevant for women within labor markets that are geographically dispersed and there are few local firms competing for their labor.

A stronger home bias among women can have adverse effects on their sorting into different locations and occupations, leading to a reduction in aggregate productivity. Misallocation of talent due to such sorting patterns has been shown to be significant in other labor market sorting models and has implications for overall economic outcomes. For instance, using a Roy model of occupational choice, Hsieh, Hurst, Jones, and Klenow (2019) find that improved talent allocation, resulting from reduced discrimination against women and African-Americans, contributed up to 40% of the growth in per capita GDP in the United States between 1960 and 2010. Similarly, in a Roy model of location choices, Bryan and Morten (2019) find that removing barriers to mobility would increase aggregate productivity by 22% in Indonesia. Furthermore, in a quantitative migration model for France, Zerecero (2021) demonstrates that eliminating home bias alone could increase output by 11%. Our paper contributes to the literature by focusing on location decisions as a factor of employment misallocation for women and studying their interaction with labor market power.

When firms have labor market power, they pay lower wages to those workers that are easier to retain even if there are no differences in marginal productivities. This monopsony power in the labor market can arise due to search frictions (Heise and Porzio, 2019; Jarosch, Sorkin, and Nimczik, 2019) or due to workers' differentiated preferences to work at different firms (Berger, Herkenhoff, and Mongey, 2022; Azkarate-Askasua and Zerecero, 2022). An important element of differentiation across firms is their location, as a worker needs to migrate to work in firms that are far away from her home location. However, the role of geography in recent papers on monopsony power has been limited to defining local labor markets, ignoring its effect on location decisions and their interaction with the wage-setting process.

If women have stronger attachments to their home locations, employers may exert a higher degree of market power over them compared to men. This implies that differences in labor supply elasticities across genders arise from differentiated home bias, rather than assuming innate differences in labor supply elasticities as in Caldwell and Oehlsen (2018). Our project will contribute by examining how much the differential employer labor market power contributes to both the gender wage gap and the resulting misallocation of men and women to jobs.

In what follows he briefly present the data and soe empirical evidence fo France that women are more attached to their home location than men. We then propose a quantitative spatial model with home bias and labor market power. WE provide a simple numerical illustration to show the different channels contributing to the gender wage gap, and how labor market power amplifies it. We leave the identification and estimation of the full model for next iterations of the paper.

2 Data

Most of our analysis relies on French administrative data *Déclaration Annuelle des Données, fichier Postes (DADS Postes)* for the years 2002-2010 and 2012-2017. The data is a repeated cross section that contains information on the workers' age, gender, wage, department of birth, firm and plant identifiers, the department of residence, occupation and industry. We do not include 2011 as the birth department is missing. The data also contains information on lagged wage, department of residence, occupation and industry. Therefore we are able to follow the flows of workers across residence, industries and occupations over time.

The unit of observation is a job which is a match between a worker and a plant times an occupation. A worker can have several jobs during a year and starting in 2002 there is main-job indicator (*Poste principale*). We focus only on main jobs and further restrict the sample to workers that were born and live in mainland France, working in a private firm and aged between 20 and 60 years. The final sample consists of more than 128 million jobs.

We additionally have information on the starting and end dates of a match which allows to identify the switchers, workers that changed jobs within a year even if potentially did not migrated. Throughout the analysis, we will aggregate the heterogeneous departments to more comparable geographical units following the aggregation in Zerecero (2021) that leads to 73 locations. We also use data on Consumer Price Index data to deflate nominal variables.[1]

2.1 Summary statistics

Table 1 presents summary statistics of the final sample. Among the population presented in the table, workers leaving their birthplace location are youngest with 30.69 years while overall migrants (returning to their birthplace or going anywhere else) are older on average with approximately 34 years. Women have lower migration shares than men, 0.39% and 0.57% respectively. Conditional on switching migration shares are higher but the gender differences remain.

Table 1: Summary Statistics

	Age		Women	Men
Non-Native Migrants	34.87	Migration cond. Switch	1.38%	2.41%
Leave BP	30.69	Migration	0.39%	0.57%
Native Switchers	33.64			
Return BP	34.33			
All	39.87			

We define a labor market m based on industry and occupation combinations. Table 2 presents summary statistics about the gender gap and average market concentration per 1-digit occupations. The average gender gap of log wages is highest for *Top management* workers. Those also present the highest average Ellison-Glaeser (EG) index that measures the geographical concentration of labor markets. All the labor markets have low levels of firm concentration measured by the average Herfindahl-Hirschman Index (HHI).

3 Empirical evidence

We start by documenting that labor flows are tilted towards the birthplace and especially so for women. First we compute labor flows from origin i to destination j per birthplace b and year t, $L^{i,j}_{b,t}$. Focusing on workers from a given birthplace that migrated, we can compute the conditional

[1]The source is https://www.insee.fr/fr/statistiques/serie/001643154.

Table 2: Summary Statistics: Occupations

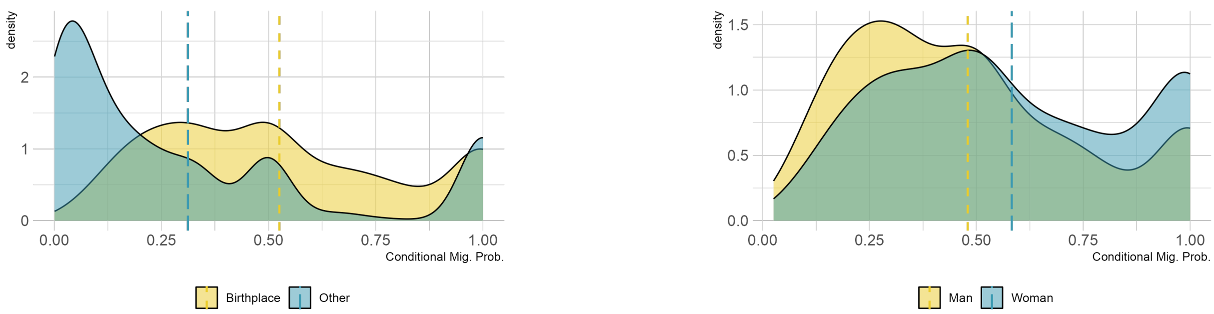
Occupation	Gap log(w)	EG index	HHI
Farmers	0.09	0.08	0.07
Firm owners, CEO	0.18	0.05	0.03
Top management	0.19	0.10	0.05
Employees supervisor level	0.16	0.03	0.04
Clerical employees	0.09	0.02	0.02
Blue collar	0.17	0.03	0.03

migration shares from origin i to destination j as:

$$s_{b,t}^{i,j} = \frac{L_{t,b}^{i,j}}{\sum_{k \neq i} L_{t,b}^{i,k}}.$$

Figure 1 presents densities of the conditional migration shares. Panel (a) shows the density of the conditional migration shares returning to birthplace versus going to any other location for the whole sample. Similarly to what was documented in Zerecero (2021), the figure clearly shows that migration patterns are biased towards the birthplace. In panel (b) we restrict to the conditional migration shares returning to the birthplace but split the sample by gender. The figure shows that mobility patterns are more strongly tilted to the birthplace for women as the return conditional migration shares are higher.

Figure 1: Conditional migration



(a) All

(b) Birthplace comparison

Notes: The left panel presents conditional migration shares to the birthplace and to any other location for the whole sample. The dashed line shows the average conditional migration share to the birthplace while the long-dashed line shows the average conditional migration share to any other location. The righ panel shows the densities of the conditional migration shares per gender. The dashed line is the average conditional migration share of returning to the birthplace for men while the long-dashed line is the analogous for women.

The fact that labor flows are tilted towards the birthplace could stem from traditional migration costs where workers remain close to where they start their career. To disentangle between traditional migration costs from the effect of birthplace we estimate the following Poisson regression separately for men and women:

$$L_{t,b}^{i,j} = exp(\mathcal{O}_{t,i} + \mathcal{D}_{t,j} + \mathbb{1}_{j \neq b}(\alpha_1 + \beta_1 \log(d_{b,j})) + \varepsilon_{t,b}^{i,j}) \qquad (1)$$

where $\mathcal{O}_{t,i}$ is an origin-year fixed effect, $\mathcal{D}_{t,j}$ is a destination-year fixed effect, $\mathbb{1}_{j \neq b}$ is an out-of-

Table 3: Gravity with birthplace

	Women		Men	
Dep. variable: $L^{i,j}_{t,b}$	Km	Hours	Km	Hours
$\log(d_{b,j})$	-1.180	-1.383	-1.136	-1.330
	(2e-04)	(2e-04)	(3e-04)	(3e-04)
Observations	5,254,394	5,254,394	5,254,394	5,254,394
Adj. Pseudo R^2	0.935	0.965	0.965	0.965

Notes: Standard errors in parenthesis. We use the distances across location pairs computed by Zerecero (2021) using Google Maps.

birthplace indicator and $\log(d_{b,j})$ is the log of distance between the birthplace b and destination j.

The results from estimating (1) via Poisson pseudo maximum likelihood are in Table 3. The first two columns show results for women while the results for men are in the last two columns. All the estimates from $\log(d_{b,j})$ are negative suggesting that the biased migration flows from Figure 1 do not only reflect migration costs but workers dislike moving away from their birthplace. If we now compare the absolute values of the estimates for men and women, we see that the women have roughly 4% higher elasticity irrespective of the measurement of the distance in kilometers or hours. Table 4 in the Appendix show that the results are robust to controlling for distance between origin and destination as in traditional gravity regressions.

4 A Model of Home Bias and the Gender Wage Gap

This section presents a quantitative spatial model where workers from different groups have a home bias decision in their location decision.

The economy consists of a set of distinct labor markets, denoted as $\mathcal{K} = 1, \ldots, K$. Each market k is comprised of a discrete set of firms, represented by $\mathcal{I}_n = 1, \ldots, I_n$. These firms are distributed across various regions, denoted by $\mathcal{R} = 1, \ldots, R$.

Each worker in the economy is born in a specific location, indexed by $b \in \mathcal{R}$, and belongs to a particular group $g \in \mathcal{G}$. A group can be defined by a combination of exogenous characteristics such as gender and age. We assume there is a finite number of workers in each birthplace and group.

Assuming a finite number of workers deviates from the standard assumption in the literature, which typically considers a continuum of workers. The key implication of this assumption is that, unlike in the case of a continuum of workers where the share of workers in a firm is equal to the probability, with discrete workers, the share of workers becomes a random variable.[2] The assumption of a finite number of workers enables a cleaner connection to the data and a more straightforward identification and estimation strategy later on.

Workers derive utility from consuming both a housing good and a freely traded final good produced by firms. Additionally, workers experience a disutility when living in a region that differs from their birthplace, reflecting a home bias in their location decisions. These disutilities are specific to each worker's birthplace and group.

[2] More formally, in the case of a continuum of workers, the share is almost surely equal to the probability.

In addition to their birthplace and group, workers exhibit heterogeneity in both their abilities and preferences regarding employment in different firms and markets. We assume that the labor decision process consists of two steps: First, workers observe idiosyncratic preference shocks and decide which labor market to participate in. Then, conditional on the market decision, workers observe both efficiency and preference shocks to determine which specific firm to work for.

Within each labor market, firms require a certain number of efficiency units of labor and offer wages per efficiency unit. Firms have the ability to discern the birthplace and group affiliation of their workers, and they leverage this information by offering different wages based on a worker's birthplace and group.

4.1 Workers

There is discrete number of workers $L^{b,g}$ for every collection of workers with birthplace b and belonging to group g. A worker ι born in b, from group g, working for firm i in location r supplies their efficiency units of labor $\exp(\theta_\iota)$ and gets paid a wage per efficiency unit $w_i^{b,g}$.

Workers use their labor income to consume a local composite good C_r, with price P_r, The budget constraint for worker ι is:

$$P_r C_{r,\iota} = w_i^{b,g} \exp(\theta_{i,\iota}).$$

The composite good $C_{r,\iota}$ is a Cobb-Douglas aggregate of a housing good $H_{r,\iota}$, inelastically supplied in region r and a final freely tradable good Q_ι:

$$C_{r,\iota} = (Q_\iota)^{1-\alpha} (H_{r,\iota})^{\alpha}.$$

Denote the housing price in region r as $P_{H,r}$, while we normalize to one the price of the final good Q. Let $N_i^{b,g}$ be the total efficiency units of labor in firm i of workers from birthplace/group b, g and $N_r \equiv \sum_{b,g} \sum_{i \in r} N_i^{b,g}$ be the sum of efficiency units in location r. Also, denote as H_r the total supply of housing in location r. Then, summing the demand for housing for all workers in location r we get:

$$\alpha w_r N_r = P_{H,r} H_r,$$

where

$$w_r N_r \equiv \sum_{b,g} \sum_{i \in r} w_i^{b,g} N_i^{b,g}.$$

Then, the price index P_r is equal to:

$$P_r = \left(\frac{1}{1-\alpha}\right)^{1-\alpha} \left(\frac{w_r N_r}{H_r}\right)^{\alpha}.$$

The expression above shows that the price index P_r depends positively on the total income in location r and negatively in the housing supply, effectively acting as a dispersion force in the model.

Worker ι with birthplace b from group g working in firm i gets the following utility:

$$\log (C_{r,\iota}) + z_{1,i,\iota} + z_{2,k(i),\iota} + \log \left(1 - \tau_{b,r(i)}^{g}\right).$$

Here, $z_{1,i,\iota}$ and $z_{2,k(i),\iota}$ represent preference shocks for working in firm i and market $k(i)$ respectively. The functions $k(i)$ and $r(i)$ indicate the market and region to which firm i belongs. The parameter $\tau_{b,r(i)} \in [0,1]$ represents the degree of disutility experienced by a worker from group g, born in birthplace b, when working in location $r(i)$. By substituting the budget constraint into the expression above we get the indirect utility for worker ι:

$$\mathbf{v}_{i,\iota} = \log\left(w_i^{b,g} \big/ P_{r(i)}\right) + \theta_{i,\iota} + z_{1,i,\iota} + z_{2,k(i),\iota} + \log\left(1 - \tau_{b,r(i)}^{g}\right).$$

At the beginning of each period, workers first observe all the vector of posted wages plus a vector of preference shocks $z_{2,k}$ for the different labor markets. With this information, workers choose the market to participate that maximizes their expected utility. Then, they observe efficiency and preference shocks θ_i and $z_{1,i}$ for the different firms and choose the firm that maximizes their utility.

As Dingel and Tintelnot (2021) mention, a key challenge when modeling a finite number of workers is that each individual decision affects equilibrium prices and wages. If workers would have rational expectations they would consider every possible combination of the other worker's choices. In the interest of tractability, we follow Dingel and Tintelnot's suggestion and assume that workers have common point-mass beliefs on prices P_r.[3] Specifically, we assume that, given the model parameters, workers hold beliefs about prices that correspond to the prices in a model with a continuum of workers.[4] Denote the vector of beliefs about prices by $\{\tilde{P}_r\}$.

We assume that the idiosyncratic efficiency shocks θ_i and the preference shocks $z_{2,k}$ are distributed Gumbel with means zero and variances $\frac{\pi^2}{6}\frac{1}{\lambda^2}$ and $\frac{\pi^2}{6}\frac{1}{\eta^2}$, respectively. The distribution of the shock $z_{1,i}$ is a the conjugate of the extreme value Type 1 distribution (see Cardell, 1997) such that $\theta_i + z_{1,i}$ is also distributed Gumbel with mean zero and variance $\frac{\pi^2}{6}\frac{1}{\varepsilon^2}$, where $\lambda \geq \varepsilon$.

With these assumptions we get that the probability of a worker born in b from group g to work in firm i in market k is:

$$p_i^{b,g} = \underbrace{\frac{\left(w_i^{b,g} \big/ \tilde{P}_{r(i)}\right)^{\varepsilon}\left(1 - \tau_{b,r(i)}^{g}\right)^{\varepsilon}}{\sum_{j\in k}\left(w_j^{b,g} \big/ \tilde{P}_{r(j)}\right)^{\varepsilon}\left(1 - \tau_{b,r(j)}^{g}\right)^{\varepsilon}}}_{p_{i|k}^{b,g}} \times \frac{\left(\Phi_k^{b,g}\right)^{\frac{\eta}{\varepsilon}}}{\Phi},$$

where

$$\Phi_k^{b,g} \equiv \sum_{j\in k}\left(w_j^{b,g} \big/ \tilde{P}_{r(j)}\right)^{\varepsilon}\left(1 - \tau_{b,r(j)}^{g}\right)^{\varepsilon}, \text{ and } \Phi \equiv \sum_{k'}\left(\Phi_{k'}^{b,g}\right)^{\frac{\eta}{\varepsilon}},$$

with $p_{i|k}^{b,g}$ being the probability of working in firm i conditional on choosing market k, and

$$p_k^{b,g} \equiv \frac{\left(\Phi_k^{b,g}\right)^{\frac{\eta}{\varepsilon}}}{\Phi}$$

is the probability of choosing market k.

[3]Here we do not need to make an assumption about the beliefs of wages, as these are posted by the firms and observed by the workers before they make their decisions regarding where to work.

[4]Dingel and Tintelnot (2021) label these beliefs "continuum-case rational expectations" because these beliefs would be rational if there were a continuum of workers.

Given this setup, we get that the expected number of workers in firm i from birthplace/group b, g is equal to $p_i^{b,g} L^{b,g}$.

4.2 Firms

As there are a finite number of workers, the total efficiency units a firm can hire for a given posted wage is a random variable. For every birthplace/group pair, the firm chooses the wages per efficiency unit that maximizes its expected profits. More formally, firm i solves the following problem:

$$\max_{\{w_i^{b,g}\}_{b\in\mathcal{R},g\in\mathcal{G}}} \quad A_i \sum_b \sum_g \mathbb{E}\left(N_i^{b,g}\right) - \sum_b \sum_g w_i^{b,g} \mathbb{E}\left(N_i^{b,g}\right),$$

where A_i represents the productivity of firm i, and $\mathbb{E}\left(N_i^{b,g}\right)$ denotes the expected efficiency units of workers from birthplace b and group g working in firm i. The following proposition would be useful when computing the expected efficiency units.

Proposition 1. *The conditional distribution of the efficiency unit* $\exp(\theta_i)$ *for a worker from birthplace/group* b, g *who chooses to work at firm i within market k follows a Fréchet distribution with dispersion parameter* λ *and mean* $\mathcal{C}\lambda\left(pi|k^{b,g}\right)^{-\frac{1}{\lambda}}$*, where* $\mathcal{C}_\lambda \equiv \frac{\Gamma(1-\frac{1}{\lambda})}{\exp(\bar{\gamma}/\lambda)}$*, with* $\Gamma(\cdot)$ *is the Gamma function and* $\bar{\gamma}$ *is the Euler-Mascheroni constant.*

The proposition shows that the variance of the efficiency units of the workers who choose to work in firm i is equal to the variance of the unconditional distribution of efficiency units. However, the mean is a decreasing function of the probability to work in firm i. With this information, we can compute the expected value of efficiency units:

$$\mathbb{E}\left(N_i^{b,g}\right) = \mathbb{E}\left(\exp(\theta_i)|i \text{ is chosen}\right)\mathbb{E}\left(L_i^{b,g}\right) = \mathcal{C}_\lambda\left(p_{i|k}^{b,g}\right)^{\frac{\lambda-1}{\lambda}}\mathbb{E}\left(L_k^{b,g}\right),$$

where $\mathbb{E}\left(L_k^{b,g}\right) \equiv p_k^{b,g} L^{b,g}$ is the expected number of workers in market m with birthplace b from group g.

We assume the firm acts strategically when posting its wages, but take as given the economy wide constant Φ.[5] With this setup, the first order conditions of the firm lead to the following expression:

$$w_i^{b,g} = \underbrace{\frac{e_i^{b,g}}{e_i^{b,g}+1}}_{\mu_i^{b,g}} A_i,$$

where

$$e_i^{b,g} \equiv \frac{\partial \log \mathbb{E}\left(N_i^{b,g}\right)}{\partial \log w_i^{b,g}} = \varepsilon\frac{\lambda-1}{\lambda}(1-p_{i|k}^{b,g}) + \eta p_{i|k}^{b,g}$$

is the elasticity of the expected efficiency units $\mathbb{E}\left(N_i^{b,g}\right)$ with respect to the efficiency wage $w_i^{b,g}$. Therefore, we have the standard expression where the wage per efficiency unit is equal to a mark-

[5]We can rationalize this behavior by assuming a myopic behavior by the firms or assuming a continuum of local labor markets.

down $\mu_i^{b,g}$ times the marginal product of an efficiency unit, and the markdown is a function of the elasticity $e_i^{b,g}$.

There are three important observations regarding the labor supply elasticity $e_i^{b,g}$. First, as long as $\eta < \varepsilon\frac{\lambda-1}{\lambda}$, then the elasticity is decreasing in the conditional probability $p_{i|k}^{b,g}$. So when the home bias is strong and there is a higher probability for workers from birthplace b to work in firm i if it is located in their birthplace, the elasticity decreases. This implies that workers are less responsive to changes in wages and exhibit a lower elasticity of labor supply. Consequently, lower elasticities result in lower markdowns

Second, let's consider the scenario where $\lambda \to \infty$. In this case, there are no variations in efficiency units across different firms, and workers choose their workplace solely based on their preference shocks. The labor supply elasticity would then be given by $\varepsilon(1-p_{i|k}^{b,g}) + \eta p_{i|k}^{b,g}$, which coincides with the elasticity in Azkarate-Askasua and Zerecero (2022) where there are only preference shocks.

Third, consider the case where $\lambda = \varepsilon$, which is equivalent to not having a preference shock $z_{1,i}$. In this situation, the elasticity becomes $(\varepsilon-1)(1-p_{i|k}^{b,g}) + \eta p_{i|k}^{b,g}$. The difference between having the term $(\varepsilon - 1)$ instead of just ε, as observed in the previous case, arises because as the marginal worker joining firm i becomes less productive, the wage increase required to raise one efficiency unit of labor must be higher compared to a scenario where workers are equally productive. This implies a more inelastic supply of efficiency units.

4.3 Wage decomposition

We can do the following decomposition of the log equilibrium expected wages:

$$
\begin{aligned}
\mathbb{E}\left(\log(w_i^{b,g}\theta_i)|\text{choose } i\right) &= \log(w_i^{b,g}) - \frac{1}{\lambda}\log(p_{i|k}^{b,g}) \\
&= \frac{\lambda-\varepsilon}{\lambda}\log(w_i^{b,g}) - \frac{\varepsilon}{\lambda}\left(\log\left(1-\tau_{b,r(i)}\right) - \log\tilde{P}_r(i)\right) + \frac{1}{\lambda}\log\Phi_k^{b,g} \\
&= \frac{\lambda-\varepsilon}{\lambda}\left(\log A_i + \log\mu_i^{b,g}\right) - \frac{\varepsilon}{\lambda}\left(\log\left(1-\tau_{b,r(i)}\right) - \log\tilde{P}_r(i)\right) + \frac{1}{\lambda}\log\Phi_k^{b,g}. \qquad (2)
\end{aligned}
$$

This expression highlights that the expected wage for workers from birthplace/group b, g depends on five elements: i) Productivities of firms, ii) Markdowns, iii) Home bias, iv) Price beliefs, and v) Option values.

When $\lambda = \varepsilon$, representing a scenario without preference shocks in the workers' firm choice, the productivity and markdown terms disappear. This reflects the standard result in the context of extreme value distributions, where expected utility is equalized among individuals of the same birthplace/group.[6] In this case, the gap between expected utility and expected log wages is solely captured by the home bias term $\log\left(1-\tau_{b,r(i)}\right)$. This implies that differences in expected wages for workers from the same birthplace/group, within the same market but different firms, are entirely explained by variations in the home bias term, which depend solely on the geographical location of the firms rather than their characteristics. However, we consider this feature undesirable. By introducing the additional preference shock $z_{1,i}$, we break this result and demonstrate that average

[6] This is common result in all the models that use extreme value distributions such as Gumbel or Fréchet. For example, in the trade model of Eaton and Kortum (2002) the average price of goods imported by a particular country is the same across all source countries. The margin of adjustment, reflecting the competitiveness of a source country, is determined by the quantity of goods it exports to the destination country, with each additional unit becoming more expensive.

wages also depend on the productivities and markdowns of each firm.

The third term, the home bias term, represents a compensating differential that firms must offer in equilibrium to attract workers born in b. As the marginal worker becomes less productive, the higher the home bias $\tau_{b,r(i)}$, the fewer workers are inclined to join firm i. This leads to an increase in the average productivity of workers in firm i. The price belief term also works as a compensating differential: workers would only choose to work in a location with a high cost of living if the corresponding wages are also high.

The fifth term, $\log \Phi_k^{b,g}$ reflects the attractiveness, in terms of expected utility, of working in market k. This term also captures the efficiency of sorting within market k for workers from birthplace/group b, g. Although the presence of home bias affects this term, the market power of firms can amplify the impact of home bias and further diminish its value. It can be shown that, given the same set of price beliefs $\tilde{P}_r$, a perfectly competitive environment with no home bias would result in a higher value for $\log \Phi_k^{b,g}$.

4.4 Equilibrium

We first define the labor market equilibrium taken as given the price beliefs $\{\tilde{P}_r\}$. Later on we define the equilibrium in the continuum-case model, which pins down the price beliefs.

Given the constant returns to scale assumption in the firms' production function, and given a vector of beliefs for prices $\{\tilde{P}_r\}$, we can characterize independently the equilibrium wages and the conditional probabilities for each market. The following proposition characterizes the equilibrium in each labor market.

Definition 1 (Labor market equilibrium). *For a given vector of beliefs $\{\tilde{P}_r\}$, a labor market equilibrium is a set of posting wages $\{w_i^{b,g}\}$ such that the following equations are satisfied for all firms i within labor market k:*

$$\begin{aligned} w_i^{b,g} &= \frac{e_i^{b,g}}{e_i^{b,g}+1} A_i, \\ e_i^{b,g} &= \varepsilon \frac{\lambda-1}{\lambda}(1-p_{i|k}^{b,g}) + \eta p_{i|k}^{b,g}, \\ p_{i|k}^{b,g} &= \frac{\left(w_i^{b,g} \big/ \tilde{P}_{r(i)}\right)^{\varepsilon} \left(1-\tau_{b,r(i)}^{g}\right)^{\varepsilon}}{\sum_{j\in k}\left(w_j^{b,g} \big/ \tilde{P}_{r(j)}\right)^{\varepsilon} \left(1-\tau_{b,r(j)}^{g}\right)^{\varepsilon}}. \end{aligned}$$

Proposition 2 (Existence and uniqueness of labor market equilibrium). *For a given vector of beliefs $\{\tilde{P}_r\}$, if $\eta < \varepsilon\frac{\lambda-1}{\lambda}$, there exists a unique labor market equilibrium.*

With the solution for the posting wages and given some price beliefs, we can characterize the probability of working in each market k. Together with the conditional probabilities, we can also characterize the unconditional probability of working in each firm for workers from every birthplace/group.

DEFINITION GRANULAR EQUILIBRIUM.

Definition 2 (Continuum-case equilibrium). *Given a measure of workers $\{L^{b,g}\}$ and housing supplies $\{H_r\}$, a continuum-case equilibrium is a set of wages $\{w_i^{b,g}\}$ and prices $\{\tilde{P}_r\}$ such that:*

1. *Constitutes a labor market equilibrium;*

2. *Satisfy the following equations:*

$$N_i^{b,g} = \mathcal{C}_\lambda \left(p_{i|k}^{b,g}\right)^{\frac{\lambda-1}{\lambda}} p_k^{b,g} L^{b,g},$$
$$P_r = \left(\frac{1}{1-\alpha}\right)^{1-\alpha} \left(\frac{\sum_{b,g}\sum_{i\in r} w_i^{b,g} N_i^{b,g}}{H_r}\right)^{\alpha},$$

for all markets k for workers from birthplace/group b, g and locations r.

5 Numerical illustration

To gain some intuition into the impact of home bias on the gender wage gap and its interaction with labor market power, let's consider a simplified numerical illustration. In this illustration, we make several simplifying assumptions. We assume there is only one labor market with two symmetrically located firms, which are identical except for their location. We consider two groups: men and women, and assume that men have no home bias ($\tau^M_{b,r(i)} = 0$), while women have a home bias when working outside their birthplace ($\tau^W_{b,r(i)} > 0$). For simplicity, we assume there is a continuum of workers from each birthplace/gender, all of the same size. Additionally, we assume no housing consumption ($\alpha = 0$), resulting in no price differences across regions. We set the parameters $\lambda = 4$ and $\varepsilon = 3$.

Figure 2 illustrates the decomposition of the gender wage gap using Equation 2 for different values of the home bias $\tau_{b,r(i)}$ for women. Note that the equation represents the average wage within each firm, and the average wage per gender would be a weighted average of these firm averages, with the weights determined by the employment share in each firm. The figure shows the difference between the average log wages of men and women.

As depicted in Figure 2, an increase in the home bias (i.e., higher values of $\tau^W_{b,r(i)}$) leads to an increase in the gender wage gap, indicated by the upward-sloping blue line. This suggests that home bias exacerbates the gender wage gap. However, the direct effect of the home bias decreases the gender wage gap. This is because the home bias enters as a compensating differential for women. Specifically, women who work outside their birthplace should, on average, be more productive and earn higher wages compared to men

The option value, or sorting, component is the largest contributor to the gender wage gap, and its magnitude is influenced by the values of λ and ε. A larger gap between these two parameters leads to a greater contribution of markdowns to the gender wage gap. Both the option value and the markdown components positively contribute to the gender wage gap. A higher home bias among women distorts the sorting of women across different firms, resulting in lower average productivity. Additionally, a greater home bias leads to a more inelastic labor supply of women when working for firms in their home location, which is where the majority of women work. This causes the average markdown for women to be lower than that for men, ultimately leading to an increase in the gender wage gap.

Figure 3 presents the gender wage gap that would exist if firms behaved in a perfectly compet-

Figure 2: Decomposition of gender gap

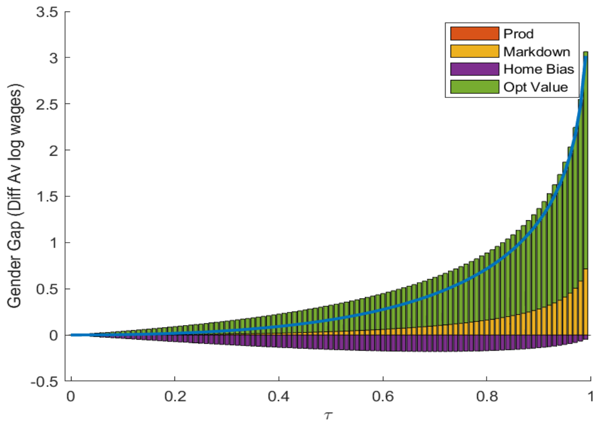
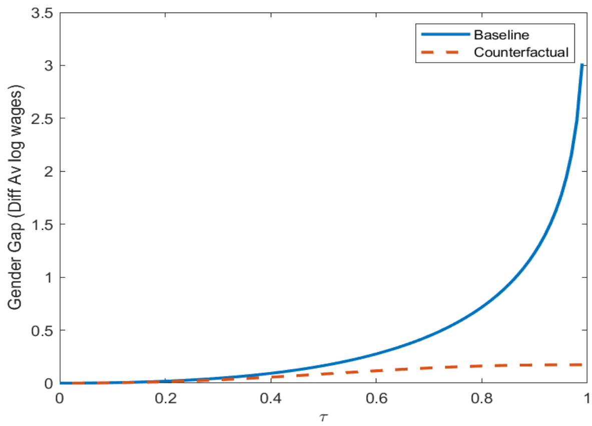


Figure 3: Gender gap in baseline and in the counterfactual



itive environment. In this scenario, firms would pay the marginal product of labor to all workers, resulting in equal wages per efficiency unit for men and women, regardless of their birthplace. The figure clearly demonstrates that the gender wage gap is much smaller when firms have no market power. In this case, the only remaining contributors to the gender wage gap are the direct effect of the home bias and the option value term. Women would still earn less than men on average because they would not pursue their comparative advantage based on income differences as strongly as men do.

6 Identification and Estimation

TBD

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Table 4: Gravity with birthplace

	Women		Men	
Dep. variable: $L_{t,b}^{i,j}$	Km	Hours	Km	Hours
$\log(d_{i,j})$	-2.170	-2.484	-1.067	-2.224
	(0.003)	(0.003)	(0.003)	(0.002)
$\log(d_{b,j})$	-1.180	-1.383	-1.136	-1.330
	(3e-04)	(3e-04)	(3e-04)	(3e-04)
Observations	5,254,394	5,254,394	5,254,394	5,254,394
Adjusted R^2	0.935	0.965	0.965	0.965

Notes: Standard errors in parenthesis. We use the distances across location pairs computed by Zerecero (2021) using Google Maps.

Appendix

A Additional empirical results

The fact that labor flows are tilted towards the birthplace could stem from traditional migration costs where workers remain close to where they start their career. To disentangle between traditional migration costs from the effect of birthplace we estimate the following Poisson regression separately for men and women:

$$L_{t,b}^{i,j} = exp(\mathcal{O}_{t,i} + \mathcal{D}_{t,j} + \mathbb{1}_{j \neq b}(\alpha_1 + \beta_1 log(d_{b,j})) + \mathbb{1}_{j \neq i}(\alpha_2 + \beta_2 log(d_{i,j})) + \varepsilon_{t,b}^{i,j}) \quad (3)$$

where $\mathcal{O}_{t,i}$ is an origin-year fixed effect, $\mathcal{D}_{t,j}$ is a destination-year fixed effect, $\mathbb{1}_{j \neq b}$ is an out-of-birthplace indicator, $\mathbb{1}_{j \neq i}$ is a migration indicator and $log(d_{k,j})$ is the log of distance between k and j.

Results in Table 4 show that the baseline point estimates are the same up to 3 digits even when we control for distance between origin and destination locations.