Hours Constraints and the Stalling Gender Gap*

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Abstract

After a decades-long period of convergence, the gender wage gap in US has stalled starting from the 1990's, especially at top of the wage and skill distribution. This paper proposes a new explanation for the stalling gender wage gap, and quantifies its macroeconomic implications. We develop a new framework featuring sorting and an endogenous hours choice. In the model, hours constraints arising exogenously from social norms can alter the sorting of workers into jobs. The model rationalizes the evidence by showing that the smaller but persistent differences in time constraints between men and women had a progressively larger effect due to technological changes that amplify the returns to working longer hours. We use the estimated model to quantify the macroeconomic implications of rising returns to hours on inequality and misallocation.

*We thank audiences at the University of Melbourne and the City University of Hong Kong. All errors are our own. We thank seminar audiences at HKU, Singapore Management University, Monash, WAMS (Melbourne). First Draft: May 2025.

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1 Introduction

In the past decades, socio-economic disparities between men and women have substantially reduced (Blau and Kahn (2008)). Both in US, and in other developed countries, women college enrollment has increased substantially, leading to a reversal in the education gender gap and a significant reduction in the experience gap; at the same time, women's labor force participation has surged, contributing to a decline in the earnings gap relative to their male counterparts. Taken as a whole, these trends have prompted researchers and observers to label the term *grand convergence* (Goldin (2014a)) to describe the process of reduced disparities between workers of different genders.

However, a closer look to the data reveals that most of this convergence process happened unevenly in time: the gender wage gap - defined as the difference between wages of observationally equivalent men and women - has reduced significantly, but only up to the 1990's, and largely stagnated ever since (Blau and Kahn (2008)). This fact is hard to explain in light of the above mentioned trends: if women have caught up with men in terms of skills and labor market experience, why has the process of convergence stopped? Perhaps even more puzzling, almost all of the "stalling gender gap" has occurred at the top of the skill (wage) distribution, where the beneficial effects of increased college enrollment should have been more visible. As recently pointed out by Kleven (2022), the literature has proposed a variety of explanations, but no conclusive explanation has emerged.

In this paper, we propose a novel explanation for the slowdown of the decline in the gender wage gap, and explore the macroeconomic consequences. The framework is a matching model of the labor market, where workers of different skills are assigned into different jobs based on their ability, and the hours they supply on the market. Women and men are equal in terms of skill (ability) endowments, but bear different costs of supplying long hours. The latter is meant to capture the different costs in terms of hours constraints that women bear even nowadays, and that - at least in part - originate in the household. A prominent example is the unequal division of responsibilities in child-care related duties (see e.g. Kleven (2022), for evidence on unequal costs of having a child). The assignment to different workers into jobs is then determined by production complementarities between skills, jobs, and hours, as well as exogenous forces such as hours constraints. More able workers are assigned more productive jobs if their skills are more productive there, and if their hours are worth more in those jobs. With such complementarities, the competition among workers for top jobs depends on the hours that workers are able to supply to the market.

The model rationalizes a declining - and then stalling - gender gap over the recent decades as a combination of two forces. On the one hand, more progressive societial norms and policies (e.g., parental leave policies) have promoted a less unequal division of responsibilities at home, favouring the inclusion of women into the labor force and into jobs demanding not only high skills and abilities, but also long hours. This force has contributed to the decline in the gender gap.

Through the lens of the model, we identify a countervailing force represented by technological change. New technological advancements taking place in recent decades have allowed workers to work from home and across time zones, thus causing jobs in top occupations to increasingly reward long and inflexible hours.[1] Importantly, rewards to long hours have increased in the most productive jobs more than in less productive jobs. For example, being always on call made hours more inflexible for partners at top law firms; at the same time, electronic patient databases made hours relatively more flexible for farmacists by making them more substitutable with one another. We model this force as an increasing supermodularity between hours and job attributes. As technology evolves, the marginal product of an additional hour becomes higher in top jobs, penalizing those with constraints to supplying hours. The key mechanism of the model is that when these complementarities are stronger, e.g. due to technological changes, even small hours differences between two workers with the same skill - but with different hours constraints - can translate into large differences in outcomes. This happens because of sorting: because hours (and not only skills) determine sorting in equilibrium, lower hours supplied in the job cause workers to be assigned to worse jobs, where the returns to hours are lower. Thus, in equilibrium, workers of a given skill who can supply more hours are assigned to the best jobs, while workers who are constrained get worse jobs even though they possess high abilities. It follows that if women bear more responsibilities at the household level, causing them to be more time-constrained, their allocation is worse than men's even if the underlying ability distributions are the same.

The model rationalizes the evidence through a combination of these two forces, whose strength varies over time. In particular, the persistent gender disparities in wages and hours are due to the fact that, despite women have been able to supply more hours in the market, their hours are still lower than their male counterparts; because of sorting and hours complementarities (whose strength has increased), even small hours differences that persist in modern societies translate into large differences in economic outcomes. Women that would otherwise be allocated to top jobs get worse jobs where hours constraints are less severe. Through the lens of this mechanism, the gains from the evolution towards more progressive societal norms are undone by the parallel evolution of technology. Importantly, these forces not only have first order implications on inequality, but also on aggregate output, in the spirit of Hsieh et al. (2019) and more recently Erosa et al. (2024) and Bandiera et al. (2024).

[1] Bertrand(2020) make a similar observation.

We use the model to revisit the macroeconomic and distributional implications of evolving barriers that prevent women from supplying labor in the market, by focusing on a margin that has been overlooked so far: namely, how hours matters to determine the equilibrium sorting of workers into jobs - and with it, output and within and between gender inequality. We do so by first estimating the model to match key moments on the evolution of inequality across genders, as well as novel empirical evidence on the return to long hours in top occupations. After having estimated a quantitative version of the model, we perform several counterfactuals. In particular, we ask how the gender gap would have evolved without the estimated changes in technology. This exercise is similar in spirit as Hsieh et al. (2019) ,but extends their insight to account for the estimated changes in technology. Preliminary results suggest that technological change nearly halved the overall convergence in incomes between men and women. Moreover, as highlighted in previous work, counterfactuals show that removing barriers for women (in this case, barriers are represented by different costs of supplying longer hours) leads to significant output gains. The new element emerging from the analysis is that these gains might be even larger than in a model without the hours margin: this arises precisely because of the additional output effect that longer hours supplied by women has on the overall economy. To the best of our knowledge, this is a novel and important insight that adds to the growing literature on the misallocation effects of barriers originating at home.

2 Literature Review

This paper contributes to several strands of the literature. We view this paper at the intersection between a. works in the macro literature aimed at understanding the output and misallocation costs of entry barriers b. papers that explore the causes and implications of hours flexibility across occupations and c. papers that solve assignment models with frictions.
Gender Gaps and Inflexible Hours Our findings provide a structural foundation for the *greedy jobs* hypothesis (Goldin, 2014b). While Goldin (2014b) identifies the non-linear return to hours as a key driver of the gap, we take this reward structure as a technological primitive (Mantovani, 2023) and formalize how it interacts with assignment. This mechanism offers a theoretical counterpart to the sociology literature on the stalling convergence: Cha and Weeden (2014) document that the rising wage premium for overwork (50+ hours) has counteracted gains in female human capital since the 1990s, a trend our model captures through increasing supermodularity between hours and job attributes. Furthermore, we show that hours constraints generate misallocation by distorting occupational choice, a result consistent with recent micro-evidence. Cortés and Pan (2019a) find that the gender gap

is largest in occupations that disproportionately reward long hours, while Cubas et al. (2023) show that the need for temporal coordination within firms penalizes workers with inflexible schedules. Finally, Wasserman (2023) documents that strict hours constraints causally drive occupational sorting in high-skill professions. By endogenizing the hours choice within a matching framework, we bridge these findings to show that time constraints do not merely reduce earnings conditional on the job; rather, they systematically reallocate high-ability women away from high-productivity matches.

Misallocation A large and growing number of papers explore the misallocation and output costs of barriers originating e.g. in the household (or more generally, barriers that prevent certain demographic groups to enter the labor market). Hsieh et al. (2019) studies the misallocation and output effects of eliminating a series of wedges for various demographic groups. Chiplunkar and Kleineberg (2025), Alon et al. (2025) and Kuhn et al. (2024) study the effects of gender frictions in the context of structural transformation. Bento et al. (2024) study the effect of gender-related frictions on entrepreneurship. Rendall (2017), Cavalcanti et al. (2022), Bergholt et al. (2024) and Lee (2024) study trends in the gender gaps related to the allocation of labor as well as technical change, analyzing the macroeconomic implications. In a related framework, and Bandiera et al. (2024) study the allocation of workers to jobs across countries, and how it depends on technology as well as endowments and frictions. Relative to all these works, we specifically focus on the hours channel - and how it is affected by technological change.

Hours and Occupations This paper contributes to the growing agenda on the heterogeneity of returns to hours across occupations. A series of papers (Erosa et al. (2022), Erosa et al. (2024) and Erosa et al. (2025)) focuses on the effects of allowing for heterogeneous returns to hours across occupations through the lens of a Roy model. Shao et al. (2021) and Shao et al. (2023) show empirically and theoretically the implications of heterogeneous returns to hours across firms. Relative to these papers, we contribute a framework of sorting and specifically focus on the heterogenous effects of technological change on returns to occupations over time.

Sorting Models Starting with Choo and Siow (2006), assignment frameworks with idiosyncratic shocks have been used in different settings. Galichon et al. (2019) provide a framework to solve these models for more general utility functions, encompassing Imperfectly Transferable Utility models (ITU), and provide an efficient algorithm to solve these models. Chade and Eeckhout (2016) characterize the assignment model in a stochastic setting. Porzio (2017) show that an assignment framework can provide new insights about the misallocation of talent across countries. A close framework in this sense is also Bandiera et al. (2024). Unlike these papers, which typically treat labor supply as inelastic, we introduce an endogenous hours choice into the matching function, allowing us to study how time constraints distort equilibrium sorting.

3 Motivating Facts

We now highlight the key facts motivating the analysis. Some of these facts are essentially a replication of what the literature has found, while some others are new. We start by a summary of the evidence. Unless specified otherwise, we use CPS data to produce the results.

Stalling of the gender gap The first fact, depicted in Figure 1, concerns the evolution of the gender gap across the wage distribution.

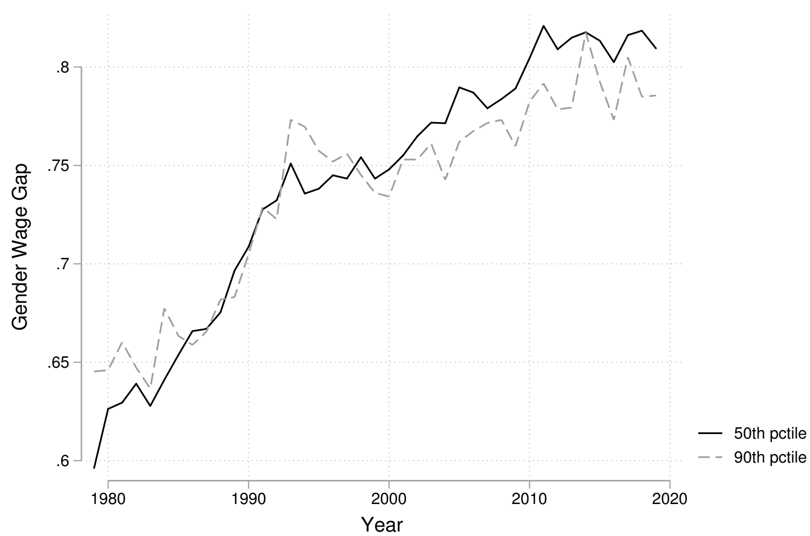

Figure 1: The evolution of the gender disparities gap across the wage distribution

As shown in the picture, the gender gap is decreasing over time (i.e., the ratio between female and male hourly wages gets closer and closer to one over time). Another message however emerges from the picture: while the growth rate of the gender wage gap is approximately stable over time for the 50th percentile of the wage distribution (black line), the growth rate at the top of the distribution (dotted line) grows rapidly until the beginning of the 1990's, and much less so afterwards. Very similar patterns emerge if, instead of considering workers across the wage distribution, we proxy for skill with years of education (see Cortes and Pan

(2019)). This picture indicates a very clear pattern: while the gender wage gap has declined over time, it has done so at different rates for differently skilled workers starting from the 1990's.

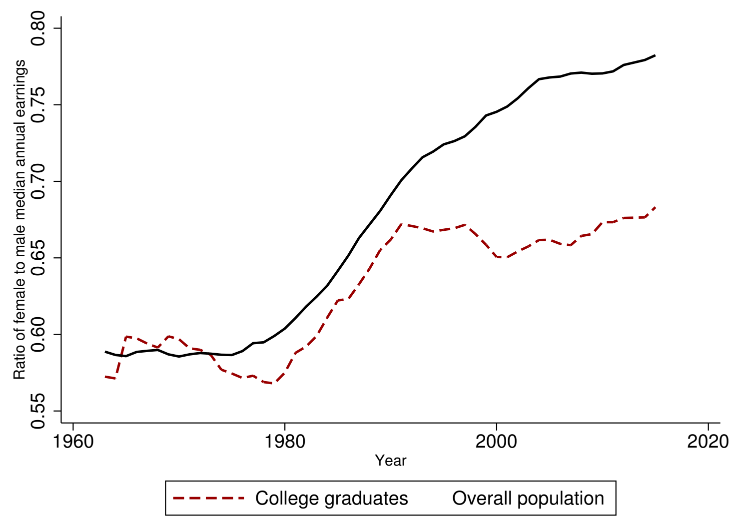

Figure 2: Female to Male Median Annual Earnings Ratio - US

In particularly, high wage workers have seen slower declines in the gender wage gap. This is particularly puzzling because if anything, we would expect women who are skilled to have been benefitted the most from the evolution of societal norms towards a more equal division of labor at home (as well as other changes in social norms that brought about similar effects).

Returns to long hours The second piece of evidence motivating the analysis is shown in Figure 3 and Figure 4. The figure is built following closely Goldin (2014a). Using data from ACS (American Community Survey), it plots the computed elasticity of annual income to weekly hours worked for college graduates against the (residualized) gender wage gap. The figure plots each invidual observation (corresponding to an occupation) and separates sectors using different markers. The main message is that gender gaps are larger in occupations where earnings are particularly elastic with respect to hours worked (i.e. where long hours are rewarded more). This picture is strongly suggestive of a link between the structure of work and how a given occupation rewards long hours, and the gap in income between men and women. This finding has motivated the literature on the gender gap to examine hours constraint as possible driver of the gender gap in the cross-section (Cortés and Pan (2019b))). Starting from the same categorization as in Goldin (2014a), we go one step further and show how this relationship has evolved over time. Given our main focus is to explain the gender gap evolution, we explore using the same data how the earnings elasticity to hours has evolved in

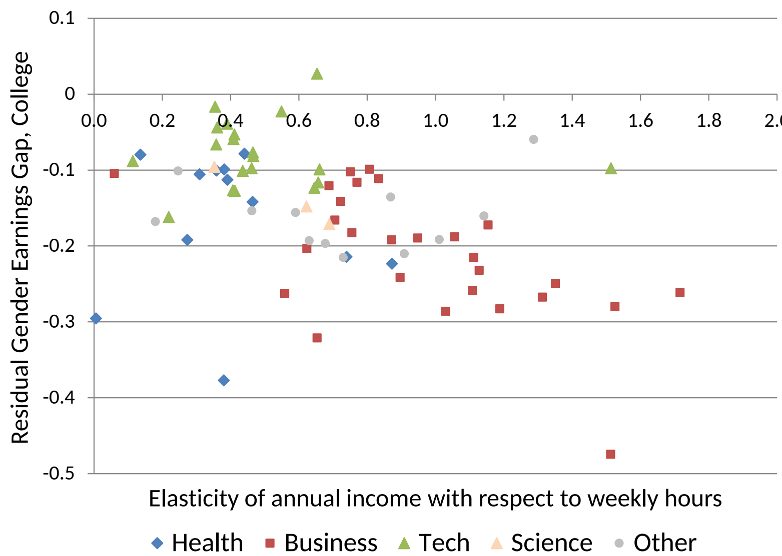

Figure 3: Elasticity of earnings to hours by occupation

the give main sectors considered by Goldin (2014a) and highlighted in the previous Figure. We plot the elasticity of earnings over time in these five sectors in Figure 4. An interesting pattern emerges from the Figure: while in 1980, the elasticity of earnings to hours was the same across all sectors, it started increasing in Business sectors (reaching a level well above one), while it stagnated or even decreased across most other sectors. This is interesting because it suggests that while we know that hours are rewarded differently depending on sectors and occupations, this is a relatively recent phenomenon and it is consistent with the story that technological change created heterogeneous rewards from long hours across workers working in different jobs. While we follow Goldin's categorization and focus on sectors, a very similar picture emerges if we instead use a more disaggregated view.

Within vs Between Evolution In light of the discussion in Erosa et al. (2022), we present one more piece of new evidence to motivate our analysis. In particular, one of their main messages is that the gender gap is predominantly a within occupation component rather than a between occupation component. Given our focus on the evolution of the gap, we explore whether the decline (and subsequent slowdown) of the gender gap has been driven by the between or the within occupation component. Figure 5 plots this decomposition.

What emerges from the picture is that both the within and between occupations component are important in explaining the evolution of the gender gap over time in US. This is an important point in light of the above discussion and of the previous literature, and suggests it is important to have a model that accounts for both elements at the same time. Because the coexistence of different rewards to long hours across occupations and large within occupation

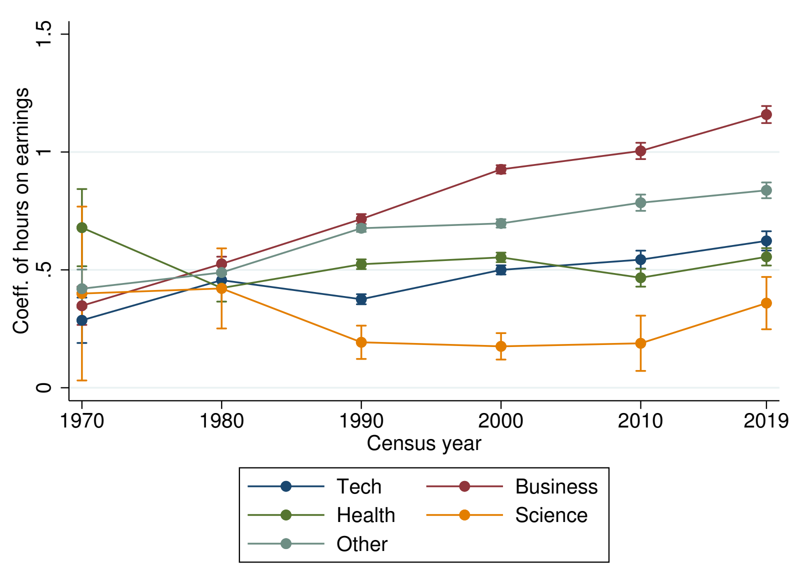

Figure 4: Elasticity of earnings to hours over time

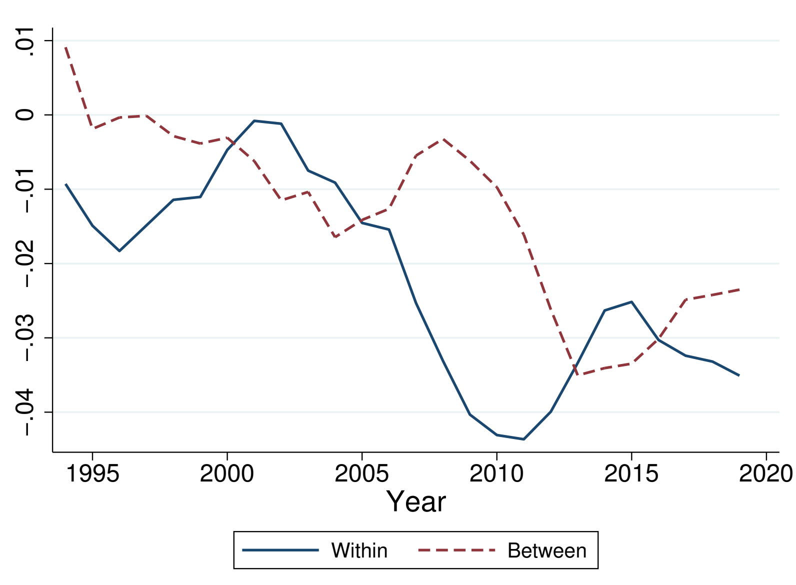

Figure 5: Within vs Between Decomposition of Gender Gap over Time - US

gaps can be explained by selection effects, our finding seems to suggest that selection effects are important in explaining the evolution (and not just the level) of the gender gap; at the same time, they are probably part of the story, and between occupation effects are as important to take into account.

Summary of the Facts Together with evidence for the US that returns to working longer hours have increased (see e.g. Kuhn and Lozano (2008)), the evidence presented thus far constitutes strong motivation to investigate the link between the stalling gender wage gap for the high skilled presented in the previous paragraph, and the rising returns to working longer hours. We summarize the evidence here:

1. The gender income gap has stalled around the 1990's; this is largely driven by workers at the top of the wage distribution and by college graduates.

2. Earnings elasticities were similar across sectors in the 1980's, and became more and more heterogeneous since. The largest increase is concentrated in business occupations.

3. The evolution of the gender earnings gap is driven by both within occupation and between occupation components.

In the next section, we present a framework to propose and characterize such link theoretically, and use it to quantify the implications of time constraints on the gender gap, output, and inequality.

4 Theory

To explain the evidence presented above, we introduce a novel model of the labor market. The model is composed of heterogeneous workers and jobs. Workers decide how much to work, and workers and jobs match based on productive attributes as well as preferences, which are idiosyncratic and random in nature. Preference shocks are of two types: shocks to preferences for partners (meant to capture different preferences of workers for different jobs) and shocks to preference for hours (to capture different desires to work long or short hours, as well as idiosyncratic factors affecting hours choices, such as health shocks). We begin by describing the basic structure of the model. For clarity, we first present the model primitives stripped down of idiosyncratic components. We then introduce idiosyncratic shocks and show how they enter the agents' problem.[2]

4.1 Baseline model

Workers The economy is composed by a fixed mass of workers, half of which are men and half of which are women. Workers are indexed by $i \in \{1, .., N^w\}$. Both men and women are endowed with a skill attribute, $x \in \mathcal{X}$, distributed according to some (discrete) cumulative

[2]The model can be thought of an extended version of the framework in Choo and Siow (2006), further developed to account for imperfectly transferable utility by Galichon et al. (2019). Relative to these frameworks, we add an endogenous hours decision.

distribution $G(\cdot)$, with mass n_x^F (for women) and n_x^M (for men). We assume $G^M(x) = G^F(x)$, i.e. men and women have the same skill (ability) distribution.

Firms There is a fixed mass of firms (jobs). Jobs are indexed by $j \in \{1, ..., N^j\}$. Jobs are heterogeneous in productivity $y \in \mathcal{Y}$, distributed according to a cdf $H(\cdot)$; each job type has mass m_y. Job productivity (like workers' ability) is assumed to be a discrete variable.

Preferences Workers' utility takes as inputs consumption and hours of work:

$$u(c, h)$$

Workers budget constraint is simply stating that consumption must not exceed income earned w, $c \leq w$.

Technology Output y takes as input workers' ability, own productivity, and workers' hours on the job:

$$\text{output } f = f(x, y, h)$$

Workers receive income w from the firm they are matched with, and firms obtain profits π, where $\pi = f - w$.
We assume for now that workers' and firms' outside option is zero. This is just a normalization and can be easily relaxed.

4.2 Adding idiosyncratic shocks

Idiosyncratic matching frictions introduce deviations from the output maximizing job allocation. This is because workers have heterogeneous preferences over jobs (and viceversa), and because of shocks to the labor supply of the workers. We now introduce such shocks to the baseline structure highlighted in the previous section.

Shocks to preferences for worker and job types We add idiosyncratic shocks to the model following Choo and Siow (2006) and in Galichon et al. (2019). Workers have idiosyncratic preferences for jobs of a given type (and analogously for jobs). One interpretation is that these shocks represent tastes for jobs (skills) of different types that do not relate to production (preference for being a teacher vs a chef) or matching frictions. This also allows for a quick and efficient solution to the model. The implication is of course that the matching function becomes a *matching probability*, in the sense that more than one worker types can be matched to the same job type (and viceversa).

The shocks' structure is the following. Both workers and jobs get additional utility from two random, i.i.d. terms ϵ_{iy} and ϵ_{jx} distributed according to a Type I EV distribution (or Gumbel):

$$\epsilon_{iy} \sim EVI(0, \sigma^{\epsilon}) \quad \forall i \text{ over all } y \in \mathcal{Y} \cup \emptyset$$

$$\epsilon_{jx} \sim EVI(0, \sigma^{\epsilon}) \quad \forall j \text{ over all } x \in \mathcal{X} \cup \emptyset$$

Therefore, ϵ_{iy} is a preference shock to a worker i for job y; similary for ϵ_{jx}.
σ^{ϵ} is a parameter that determines how much shocks determine matching; if $\sigma^{\epsilon} \to 0$, matching is uniquely characterized by worker-job complementarities; as $\sigma^{\epsilon} \to \infty$, matching is random. Finally, note that workers' preferences over jobs include the possibility that they decide to stay unmatched, i.e. workers' preferences are defined over $\mathcal{Y} \cup \emptyset$ (and analogously for jobs). We denote the choice to remain unmatched as ϵ_{i0} and ϵ_{0j}.

Shocks to preferences for hours levels We assume that hours levels are discrete and belong to a set $\mathcal{H}$, i.e. $h \in \mathcal{H}$. We denote the preference for worker i for hours level h as δ_{ih}. Because non-participation (and hence zero hours worked) are captured by the preference shocks to partners, we assume that hours levels are strictly positive. The shock to workers hours preferences δ_{ih} is assumed to be Type I EV distributed, with scale parameter σ^{δ}:

$$\delta_{ih} \sim EVI(0, \sigma^{\delta})$$

This is once again a standard formulation and follows, for example, the model in Calvo Lindenlaub and Reynoso (2024). The tractability is given once again by the assumption on the distribution of hours shocks, which will translate in an easily computable hours distribution within a match. That is, hours worked by the worker vary within a given x, y match precisely due to idiosyncratic preferences.

Timing In this section we specify the timing of the model. The model is static; however, we add shocks to preferences and hours choices so it is important to specify the within-stage timing of events.

1. Stage 1. Matching shocks: agents receive idiosyncratic preference shocks for partners (jobs). Matching probabilities are derived using the algorithm below.

2. Stage 2. Hours shocks: in a second stage, and taking the matching function as given, agents choose their labor supply subject to hours idiosyncratic preferences shocks

Notice that this timing implies that agents match based on *expected* hours; the assumption

of Type I EV shocks implies these expectations can be derived analytically in a standard way.
Also, notice that this timing structure implies that matching will be affected by agents' expected hours and therefore, agents expected to work less on average will obtain a worse job/wage, all else equal.

	first stage	second stage
shocks	workers observe ϵ_y, jobs ϵ_x	pair x, y observe δ_h
allocations	x and y match	choose hours

4.3 Equilibrium

In this section we analyze the equilibrium properties of the model, highlighting in particular how matching and labor supply interact in equilibrium.

Decisions Let's recap the problem of the workers and jobs (we leave arguments of functions implicit).
Worker i solves the problem of choosing in which job to work, and how many hours to work:

$$\max_{y \in \mathcal{Y}} \{ \max_{h \in \mathcal{H}} \{ u(c,h)) + \delta_{ih} \} + \epsilon_{iy}, \epsilon_{i0} \} \quad \text{s.t.} \quad c = w$$

Firms (jobs) solve:

$$\max_{x \in \mathcal{X}} \{ f(x,y,h) - w + \epsilon_{xj}, \epsilon_{0j} \},$$

that is, jobs choose which worker to match with. Workers' and jobs' decisions on which partner to match and produce will give rise to an equilibrium matching probability (because of idiosyncratic shocks, matching is not pure, and more than one x can match with the same y). The additional ingredient of this model is that equilibrium labor supply also affects matching because hours enter in production, and we allow for complementarities between hours and jobs (or skills).
Starting from agents' decisions and noting the stochastic nature of their problem, we can define the *average* indirect utilities as:

$$u_x = \mathbb{E}_\epsilon [\max_y \mathbb{E}_\delta \{ \max_h u(c,h)) + \delta_{ih} \} + \epsilon_{iy}, \epsilon_{i0} \}] \tag{1}$$

$$v_y = \mathbb{E}_\epsilon[\max_x\{f - w + \epsilon_{xj}, \epsilon_{0j}\}] \tag{2}$$

These the average utility associated with the best choice of y and x, respectively. Note that the expectation is taken over 'partner' taste shocks, not hours shocks.

Matching We outline the solution for the model, building on Galichon et al. (2019). The additional layer, as explained, is that there is an endogenous labor supply decision to be solved for.

Let U_{xy} be the utility of a worker of type x matched with a job of type y. Similarly, let V_{xy}be the utility of a job y matched with a worker of type x. Indirect utilities for our model, expressed in (1) and (2), can be written in more general form as:

$$u_x = \mathbb{E}_\epsilon[\max_y U_{xy} + \epsilon_{iy}, \epsilon_{i0}\}]$$

$$v_y = \mathbb{E}_\epsilon[\max_x V_{xy} + \epsilon_{xj}, \epsilon_{oj}\}]$$

Matched workers and jobs generate surplus $V_{xy} + U_{xy} = \Phi_{xy}$. Because of our assumptions on the shocks distributions, and in particular because the shocks are EV Type I distributed, we can write these two as

$$u_x = \sigma^\epsilon log(1 + \sum_y exp(\frac{U_{xy}}{\sigma^\epsilon}) \tag{3}$$

$$v_y = \sigma^\epsilon log(1 + \sum_x exp(\frac{V_{xy}}{\sigma^\epsilon}) \tag{4}$$

which imply

$$exp(-\frac{u_x}{\sigma^\epsilon}) = 1 + \sum_y exp(\frac{U_{xy}}{\sigma^\epsilon}) \tag{5}$$

and

$$exp(-\frac{v_y}{\sigma^\epsilon}) = 1 + \sum_x exp(\frac{V_{xy}}{\sigma^\epsilon}) \tag{6}$$

For simplicity, we normalize the payoff of being unmatched to be equal to 0. The model allows for a generalization in this sense. Following the standard derivations of McFadden (1974) framework, the conditional choice probability of choosing type y for a worker x can be written as:

$$\mu_{y|x} = \frac{\mu_{xy}}{n_x} = \text{Prob. that y is chosen by x} = \frac{exp(\frac{U_{xy}}{\sigma^\epsilon})}{1 + \sum_y exp(\frac{U_{xy}}{\sigma^\epsilon})} \tag{7}$$

The choice of staying unmatched is defined by:

$$\mu_{0|x} = \frac{\mu_{0x}}{n_x} = \text{Prob. that x is unmatched} = \frac{1}{1 + \sum_y exp(\frac{U_{xy}}{\sigma^\epsilon})} \tag{8}$$

For jobs y, we have the analogous probabilities as given by:

$$\mu_{x|y} = \frac{\mu_{xy}}{m_y} = \text{Prob. that x is chosen by y} = \frac{exp(\frac{V_{xy}}{\sigma^\epsilon})}{1 + \sum_x exp(\frac{V_{xy}}{\sigma^\epsilon})} \tag{9}$$

$$\mu_{0|y} = \frac{\mu_{0y}}{m_y} = \text{Prob. that y is unmatched} = \frac{1}{1 + \sum_x exp(\frac{V_{xy}}{\sigma^\epsilon})} \tag{10}$$

Putting together (5) with (7) and (6) with (9) we obtain, respectively:

$$\frac{\mu_{y|x}}{n_x} = exp(\frac{(U_{xy} - u_x)}{\sigma^\epsilon}) \tag{11}$$

$$\frac{\mu_{x|y}}{m_y} = exp(\frac{(V_{xy} - v_y)}{\sigma^\epsilon}) \tag{12}$$

Similarly, putting together (5) with (8) and (6) with (10), we obtain:

$$\frac{\mu_{0|x}}{n_x} = exp(\frac{-u_x}{\sigma^\epsilon}) \tag{13}$$

$$\frac{\mu_{0|y}}{m_y} = exp(\frac{-v_y}{\sigma^\epsilon}) \tag{14}$$

Taken together, (11) to (14) imply we can write the utilities $U_{xy}$and V_{xy}as:

$$U_{xy} = \sigma^\epsilon ln(\mu_{xy}) - \sigma^\epsilon ln(\mu_{x0}) \tag{15}$$

$$V_{xy} = \sigma^\epsilon ln(\mu_{xy}) - \sigma^\epsilon ln(\mu_{0y}) \tag{16}$$

So far, the derivation of the model is rather standard and (15) and (16) are the equations typically derived in this class of models.

It is now useful to define one more object, the *Distance to Frontier* function $D()$.

$$D(U, V) = min\{t \in \mathbb{R} : (U - t, V - t) \in \mathcal{F}\}$$

where $\mathcal{F}$ is the feasible utility set, i.e. the set of points (U, V) s.t. $\mathcal{F} = \{(U, V) : \exists w, U \leq U(w), V \leq V(w)\}$. Essentially, $\mathcal{F}$is the set of utilities that are feasible given a transfer between agents w. The function $D(U, V)$ measures how far two utilities U and V are from the frontier of $\mathcal{F}$.
It follows that at an optimum, we must have $D(U, V) = 0$, i.e. we are on the frontier of feasible utilities. In equilibrium, as just explained, we have (we use $D_{xy}$to denote the distance to frontier function for a given pair x and y):

$$D_{xy}(U_{xy}, V_{xy}) = 0 \tag{17}$$

Using (15) and (16) in (17) it follows that:

$$D_{xy}(\sigma^{\epsilon} ln(\mu_{xy}) - \sigma^{\epsilon} ln(\mu_{x0}), \sigma^{\epsilon} ln(\mu_{xy}) - \sigma^{\epsilon} ln(\mu_{0y})) = 0$$

The usefulness of this function is given by the fact that for an imprefectly transferable utility (ITU) model, we can write the equilibrium matching function as a function of unmatched agents on each side of the market, μ_{x0}, μ_{0y}. This is because of how this function is constructed. In particular, this function satisfies the property that for a real number a, we have that $D(U + a, V + a) = D(U, V) + a$; using this, we can rearrange equation (17) to get:

$$\mu_{xy} = exp(-D_{xy}(-\sigma^{\epsilon} ln\mu_{x0}, -\sigma^{\epsilon} ln\mu_{0y})/\nu) \tag{18}$$

Equation (18) is the key equation, because we have expressed the matching probability μ_{xy}as a function of unmatched agents probabilities. The function is expressed in (18) and we call it M_{xy}. In other words, $\mu_{xy} = M_{xy}(\mu_{x0}, \mu_{oy})$.
Market clearing implies that:

$$n_x = \mu_{x0} + \sum_y \mu_{xy} \tag{19}$$

$$m_y = \mu_{0y} + \sum_x \mu_{xy} \tag{20}$$

Essentially, (19) and (20) imply that the masses of agents at both sides of the market are consistent with the masses implied by equilibrium matching.
Using (18) in (19) and (20) we obtain the equations of the model:

$$n_x = \mu_{x0} + \sum_y M_{xy}(\mu_{x0}, \mu_{0y}) \tag{21}$$

$$m_y = \mu_{0y} + \sum_x M_{xy}(\mu_{x0}, \mu_{0y}) \tag{22}$$

Equations (21) and (22) are two (sets of) equations in the unknowns μ_{x0} and μ_{0y}. Now, what is left to do is to characterize $M_{xy}(\mu_{x0}, \mu_{0y})$ for this particular framework.

Equilibrium Hours Where does the hours choice enter here? In equation (18), we have used the distance to frontier function. The functional form of this (which enters in M_{xy}) depends on the (expected) surplus of the match, which in turn is stochastic because the hours choice is stochastic. In particular, take the distance to frontier function in the case in which hours are deterministic as in the baseline model. The Pareto frontier in this model is defined as:

$$U \leq u(w, h^*) = u(f - V, h^*)$$

In other words, this defines the maximum utility that a worker x gets when matched with a firm y to which it leaves utility V,at the optimal level of hours h^*. For all feasible values of V, this object defines the Pareto frontier of the match. Now, assuming that $u(c, h) = c - \psi \frac{h^{1+\nu}}{1+\nu}$, this becomes

$$U \leq f - V - \psi \frac{h^{*1+\nu}}{1+\nu}$$

where h^* is the optimal hours choice. Then, deriving $D(U, V)$ means finding the t such that $U - t, V - t$ is on the frontier, so it means solving this equation in t

$$U - t = f - (V - t) - \psi \frac{h^{*1+\nu}}{1+\nu}$$

which gives

$$t = D(U, V) = \frac{U + V - f + \psi \frac{h^{*1+\nu}}{1+\nu}}{2}$$

Note that, when there is no hours choice, the frontier simply becomes $t = D(U, V) = \frac{U+V-f}{2}$. When hours choice is stochastic, the frontier is computed from solving for t in

$$U - t = \mathbb{E}_\delta[max_h(f - V + t - \psi \frac{h^{1+\nu}}{1+\nu}) + \delta_h] \tag{23}$$

where $\mathbb{E}_\delta$ is the expectation with respect to hours taste shocks. Given our assumption on taste shocks, the expectation in (23) can be computed in closed form. So the hours choice affects the matching probabilities through the frontier function (23), which in turns enter the way we compute the equilibrium matching (see 21 and 22). The distance to frontier function becomes

$$D(U,V) = \frac{U + V - \mathbb{E}_\delta[max_h f - \psi \frac{h^{1+\nu}}{1+\nu} + \delta_h]}{2}$$

or,

$$D(U,V) = \frac{U + V - log(\sum_{h'} exp(\frac{f(x,y,h') - \psi \frac{h'^{1+\nu}}{1+\nu}}{\sigma^\delta}))}{2}$$

which is the stochastic version of the expression above. The expectation term can be computed in closed form thanks to the assumption of EVI type shocks. Notice that, if this last expression was stripped down of hours (or if there was one hours level to be chosing from), the expression for the frontier would be exactly the expression used in Bandiera et al. (2024) to characterize their matching function.

The importance of the last expression relies upon the fact that, together with (21) and (22), we can now solve for an equilibrium using the tools developed in Galichon et al. (2019). Before showing how we do that that, we provide some further intuition on the model mechanism.[3]

Analysis For a given gender, M_{xy} is given by

$$M_{xy} = exp(-D(-log\mu_{0x}, -log\mu_{y0})) = exp(-[\frac{-log\mu_{0x} - log\mu_{y0} - \mathbb{E}_\delta[max_h f - \psi \frac{h^{1+\nu}}{1+\nu} + \delta_h]}{2}])$$

or, using the property of the EV1 distribution,

$$M_{xy} = exp(\frac{log(\mu_{0x} \cdot \mu_{y0} \cdot (\sum exp(f(x,y,h') - \psi \frac{h'^{1+\nu}}{1+\nu})/\sigma^\delta)}{2})$$

which finally simplifies to

$$M_{xy} = (\mu_{0x} \cdot \mu_{y0} \cdot (\sum exp(f(x,y,h) - \psi \frac{h^{1+\nu}}{1+\nu})/\sigma^\delta)^{\frac{1}{2}}$$

Notice that $M_{xy}$is higher when the benefit of hours (embedded in f) are high for a given x, y relative to the cost, measured by $\psi \frac{h'^{1+\nu}}{1+\nu}$.

To see things even more simply, suppose there are only two hours choices, high and low.

[3] Notice that we derived these expressions without any reference to gender. This is purely for the sake of exposition, and the role of gender will be made clear in the next section. Alternatively, with some abuse of notation, one could interpret x in the previous derivation as representing a vector comprising the pure skill attribute as well as the gender of the worker, and the derivations would carry through with the same logic and expressions.

Then the matching probability of x, y

$$M_{xy} = (\mu_{0x} \cdot \mu_{y0} \cdot (exp(f(x,y,h^L) - \psi \frac{h^{L,1+\nu}}{1+\nu} + exp(f(x,y,h^H) - \psi \frac{h^{H,1+\nu}}{1+\nu} / \sigma^{\delta})^{\frac{1}{2}}$$

How do hours complementarities affect matching? Take another job now, more productive than y, and call it y'. How does $M_{xy'}$ compare to M_{xy}?

$$\frac{M_{xy'}}{M_{xy}} = \frac{(exp(f(x,y',h^L) - \psi \frac{h^{L,1+\nu}}{1+\nu}) + exp(f(x,y',h^H) - \psi \frac{h^{H,1+\nu}}{1+\nu}))^{\frac{1}{2}}}{(exp(f(x,y,h^L) - \psi \frac{h^{L,1+\nu}}{1+\nu}) + exp(f(x,y,h^H) - \psi \frac{h^{H,1+\nu}}{1+\nu}))^{\frac{1}{2}}} \tag{24}$$

Therefore, $M_{xy'} > M_{xy}$ if $f(x,y',h^H) - f(x,y',h^L) > f(x,y,h^H) - f(x,y,h^L)$, that is if the output/utility gain from moving to high hours is larger in job y'. This is precisely true when there are jobs-hours complementarities: higher hours are worth more in top jobs, so the benefit net of cost of hours in high y' is higher than in y. Of course, classic x, y complementarities play the usual role here, driving up M_{xy} for higher types.

Hours Distribution Agents' choose hours taking matching as given. The probability of choosing a given hours level is, given a match between x, y:

$$\pi(h'|x,y) = \text{Prob. that h' is chosen by x} = \frac{exp(\frac{\bar{u}_{xy}(h')}{\sigma^{\delta}})}{1 + \sum_{h'} exp(\frac{\bar{u}_{xy}(h')}{\sigma^{\delta}})} \tag{25}$$

where $\bar{u}_{xy}(h') = u(w(x,y), h')$ is the utility of a worker of type x matched with job y when choosing hours alternative h'.

Finally, note that if we assume linear utility, then the hours choice can be solved independently of the matching stage. This is because of the assumed timing and the fact that utility is linear, so different income levels will not affect the decision to work. If instead we assume nonlinear utility, the matching problem and the hours problem need to be solved together. This will be important in the solution algorithm of the model, as explained below.

Existence and Uniqueness of Equilibrium Existence and uniqueness of equilibrium is proven in Galichon, Kominers, Weber (2018) unders some assumptions that are satisfied here. Essentially, we require that workers' preferences for jobs are x-specific and not i-specific; that preference shocks have continuous support; and that utilities from matching are bounded. These conditions also guarantee that an efficient algorithm (the Iterative Projective Fit- ting Procedure, IPFP) to solve (21)-(22) exist. We will outline an algorithm below that builds on their work, but generalizes it by allowing for workers to choose how much to work.

4.4 Gender (Hours) Gap

How do we model the gender gap in hours in this framwork? Our approach will be to assume an utility of the form:

$$u(c,h) = c - \psi \frac{h^{1+\nu}}{1+\nu}$$

and impose that women have a higher ψ, i.e. $\psi^F > \psi^M$. This is a typical approach in the literature, and similar ways of assuming gender disparities originating from the household have been used frequently (Hsieh et al, 2019; Bento, Shao, Sohail, 2024). This will result in a stochastically lower hours distribution for women: $\Pi(h|x^M)$ is FOSD over $\Pi(h|x^F)$. The way to think of $\psi^F > \psi^M$ is to think that women have higher (and exogenous in this model) hours constraints. Such constraints can be thought of stemming from an unequal division of responsibilities at home. For example, these constraints can represent the implicit or explicit assignment of child-care duties to women. We do not model such within-household decisions and norms explicitly in our model. Rather, we take the view that such constraints and norms evolve over time and we take their evolution as given. Modeling endogenous household specialization and fertility related decision represents an interesting extension to the framework.

How will the (exogenous) gender gap in hours impact the equilibrium variables? To see how, recall that the matching function $M_{xy}$is a function of the (expected) gain from matching, given by $\mathbb{E}_\delta(\Phi)$. For a given x, y combination, $\mathbb{E}_\delta(\Phi)^F < \mathbb{E}_\delta(\Phi)^M$ because men provide *stochastically* higher hours than women. This implies that men of a given skill will *stochastically* get a better match than women of the same skill simply because they provide higher hours (see (24)).

Notice that this last effect is *not* linear across agents of different types. Because of complementarities in the production function, longer hours are more valuable for high x, high y. Therefore, a given constraint will translate into proportionally worse matches at the top than at the bottom. Hence the gender wage gap should be more sensitive to hours constraint at the top, which is one of our starting hypotheses.

4.5 Equilibrium Properties

We now analyze the equilibrium properties of the model. Unless otherwise noted, we use the midpoint baseline calibration of the model, which we explain in the next section. Foreshadowing the estimation in the next section, we adopt the following functional forms: for utility, we assume:

$$u(c,h) = c - \psi \frac{h^{1+\nu}}{1+\nu}$$

For production, we assume a bi-linear production function

$$f(x,y,h) = \alpha \cdot xh + \beta \cdot xy + \gamma \cdot yh$$

Hours We first look at hours distributions for men, women, and the difference between the two. The results are depicted in Figure 6. In particular, we look at probability of working longer hours. Due to positive hours complementarities ($\gamma > 0$), high skilled workers work longer hours, and this is particularly true in top jobs. This is true for both men and women. However, men work relatively *more* in top jobs than women. This is because $\psi^F > \psi^M$. This implies that men are disproportionally advantaged in jobs that require long hours. Given γ, these are top jobs.

(a) Men (b) Women (c) Δ Men-Women

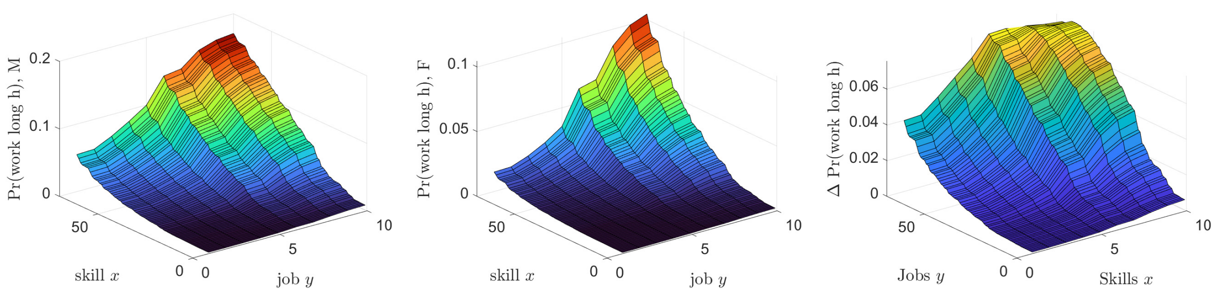

Figure 6: Probability of working long hours

Matching We now look at the equilibrium matching properties. As before, we compare men and women (but also look at them separately). Given positive type complementarities $\beta > 0$, workers with higher ability are more likely to sort into high type jobs. Therefore, the diagonal is more densely populated (i.e. there is PAM on average in the labor market). What is particularly interesting is the third panel: in particular, the model predicts that women are particularly under-represented in top jobs (there, the difference between men and women is higher). This difference is especially pronounced for skilled women. This is because skilled women are required to work longer hours; together with the higher time constraint that women have, this implies that those high-ability women who would otherwise work in top jobs, are reallocated elsewhere. For low skilled women, this is less evident: their hours are wort relatively less, so their time constraints affect their allocation relatively less.

(a) Men (b) Women (c) Δ Men-Women

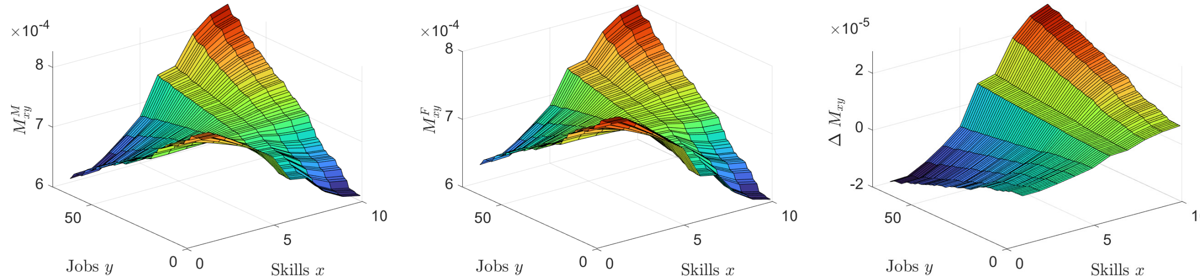

Figure 7: Matching Probability M_{xy}

Income We now look at the income of workers in different parts of the skill and jobs distributions. In light of the type and hours complementarities, it is not surprising at this point that skilled workers in top jobs earn disproportionately more. What is worth highlighting here is that the income gap is larger precisely for those workers: the percentage difference in incomes between men and women is significantly larger there. This follows naturally from the fact that hours constraints are particularly penalizing in jobs where hours matter the most; these penalties are therefore reflected in lower incomes precisely in that part of the distribution.

(a) Men (b) Women (c) Δ Women-Men (%)

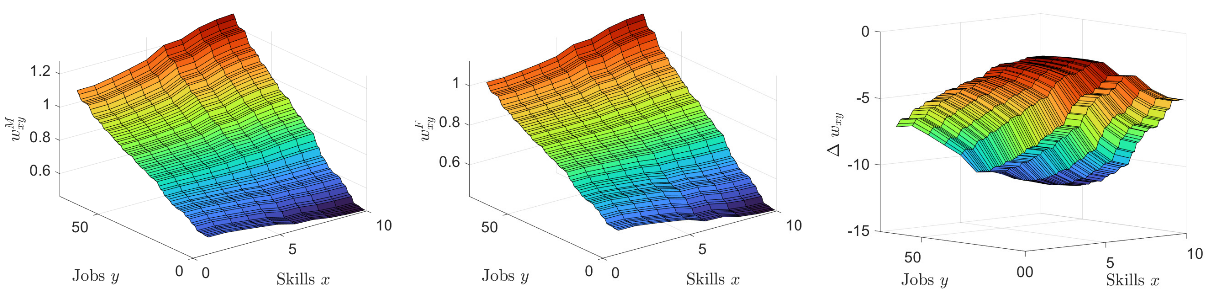

Figure 8: Income w_{xy}

Comparative Statics Before turning to the quantification of the model, we run a comparative statics exercise to further show how the model works and to preview the main counterfactuals in the next section. In particular, we ask what are the consequences - in terms of equilibrium hours, wages, and sorting - of higher hours complementarities, captured by γ. This is meant to simulate an increase in rewards to long hours in top jobs, a key component - we argue - of the technological revolution taking place in the previous decades. We plot the results in Figure 9.

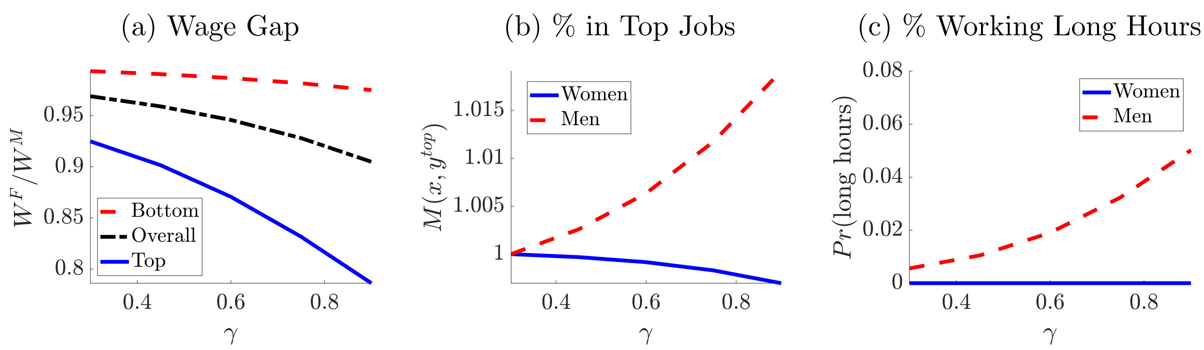

Figure 9: Technological Change

The main takeaway from the figure is that when technological change increases f_{yh} (captured by an increase in γ), it amplifies inequality by widening the gender wage gap (especially at the top of the distribution) and reducing women representation in top jobs and in roles that require long hours. The fact that the gender gap increases at different rates in the skill distribution is an interesting feature of our framework, and it speaks directly to the empirical evidence we have presented at the beginning of the previous section.

Following an increase in f_{yh}, womens' representation in top jobs declines. The hours differential between men and women naturally widens.

5 Quantification

We now turn to the quantification of the theory and the main counterfactuals. The estimation strategy is to adopt the simplestand most transparent specification that matches the key moments of interest. Importantly, we take the stand that we do not target the gender gap in the estimation. The reason behind this is that we believe there are forces that drive gender differences in wages that are not captured by either preferences or technology. We do not model such forces, but we believe they are important in driving gender gaps. We therefore evaluate what is the fraction of the gender gap that the model can endogenously explain.

5.1 Identification and Estimation

Our estimation strategy combines calibration with moment matching. We can provide an heuristic identification argument, keeping in mind all moments and parameters are jointly

$\mathbb{E}(h)^M/\mathbb{E}(h)^F$	Avg. Hours M/F
$\mathbb{E}$(w)	Avg. Wage
$\mathbb{E}\left[Var(w\|y)\right]$	Income inequality (within y)
$Std\left[(w)\right]$	Wage dispersion
$\varepsilon_{h,w}^{(y)}$	Coeff. of reg. $log(h)$ on $log(w)$ over occ. rank
$Var(h)$	Hours variance

Table 1: Summary of Targeted Moments

estimated with Simulated Methods of Moments. We calibrate the utility curvature parameter ν to 0.4, consistent with micro evidence (Violante et al., 2014). We then estimate the shock parameters σ_ϵ, σ_δ, and the female disutility parameter ψ^F (normalizing $\psi^M = 1$), together with the technology parameters α, β, and γ. The model is disciplined with microdata from the Current Population Survey, restricting the sample to full time workers ages 25 to 64 from 1980 to 2015. The six free parameters are identified by six targeted moments: the ratio of mean hours for men to mean hours for women, $\mathbb{E}(h)^M/\mathbb{E}(h)^F$; the mean wage, $\mathbb{E}(w)$; the expected within y wage variance, $\mathbb{E}[\mathrm{Var}(w \mid y)]$; the overall standard deviation of wages, $\mathrm{Std}(w)$; the elasticity $\varepsilon_{h,w}^{(y)}$, measured as the coefficient from regressing $\log h$ on $\log w$ across occupation ranks; and the variance of hours, $\mathrm{Var}(h)$. We summarize the model moments in Table 1.

5.2 Model Fit and Parameters Estimates

To evaluate model performance we compare targeted moments in 1980 and 2015. The model tracks the decline in the male to female hours ratio and reproduces average wage levels on a normalized scale in both years. It also captures broad movements in dispersion, although by the end of the sample it generates too much within y wage variance and a flatter relationship between hours and wages across occupation ranks than the data suggest. Measures of the dispersion of hours and wages are broadly consistent with the data, with a mild tendency to overstate variability in the later period. An untargeted check using the aggregate gender wage ratio indicates that the model explains about one half of the level gap in 1980 and roughly one third of the observed narrowing between 1980 and 2015. These patterns suggest that the technology and shock structure capture the main forces behind average outcomes and overall dispersion.

We now turn to the parameters estimates. We present a simple proof of concept calibration for 1980 and 2015. Aggregate productivity is normalized at $\alpha = 1$ in both years so that movements in outcomes are attributed to technology and preferences rather than level shifts. The key technological changes occur in the complementarities that govern production. The parameter β, which scales f_{xy}, rises from 0.2 to 0.55, indicating stronger sorting or complementarity between worker type and job type. The parameter γ, which scales f_{yh}, increases from 0.1 to 0.9, implying a much tighter link between hours and effective output within occupations. To keep identification transparent, the dispersion of idiosyncratic shocks is held fixed across years, with the variance of hours shocks σ_δ and the variance of partner shocks σ_ϵ kept at their calibrated values. The female disutility of work parameter ψ^F declines from 2.51 to 1.52, which we interpret as a reduction in non market costs of work and constraints that limit long hour choices for women. Taken together, these values are sufficient to reproduce the major cross year movements in hours, wage dispersion, and the gender gap documented in the data, while keeping the exercise intentionally minimal and transparent.

5.3 Counterfactuals

We conduct two main counterfactuals. The first counterfactual of interest is to examine the misallocation effects for the forces that we highlight in the model. The second counterfactual looks at the evolution of gender disparities and how they were affectd by technological change. Of course, these two sets of counterfactual are largely driven by the same forces, but we present them separately for clarity.

Output The main counterfactual regarding output is highlighted in Table 2. The exercise we conduct is the following. We normalize output at its 1980 level for comparison. Then, we feed the model with the estimated value for ψ^{2015}. Because ψ_F^{2015} reduced relative to ψ_F^{1980}, output increases (first row). This is naturally driven by the fact that women are less time constrained, and therefore better allocated. As a result, overall output increases. In line with Hsieh et al (2019), we find that there are significant output gains from reducing exogenous barriers preventing women from entering the market (in this case, these barriers aretime constraints). In the second row, we repeat the same exercise but also feeding the model with the estimated value for the hours-job complementarity in 2015, γ^{2015}. The output gains are now even larger (16%). The reason is that reducing gender disparities at home have even more beneficial effects when time on the job matters more (as in 2015, relative to 1980). The key insight is that output gains from reducing time barriers for women might be even larger than we thought.

Gender Gaps The secon counterfactual exercise asks how the gender gap would have evolved absent the technological changes we estimate. The result is in Table 3. The model correctly predicts a significant decrease in gender gaps (first column). Notice that while in

	Output (Normalized)	Output (ψ^{2015})
Fixed technology (γ^{1980})	1	1.13
With tech. change (γ^{2015})	1	1.16

Table 2: Counterfactual Economy: Output

reality the gap closed more than the model suggests, this is an untargeted model and certainly other aspects not present in the theory could have affected the evolution of the gender gap.

In column two, we feed the 1980 model with all 2015 parameters with the exception of the estimated γ, which is kept at its 1980 level. The result is striking: the gender gap would have reduced much more. In fact, this means that the gender gap evolution has been nearly halved by the technological forces we estimate and we presented in this model. This is a novel result and insight, and it is at the core of the model mechanism.

	Model (Baseline)	Model (γ^{1980})
Gender Gap (1980)	0.79	0.79
Gender Gap (2015)	0.84	0.90
Δ Gender Gap	0.05	0.11

Table 3: Counterfactual Economy: Gender Earnings Gap

6 Conclusion

This paper shows that the post 1990s slowdown in gender wage convergence can be understood through the interaction of hours constraints with sorting when hours raise productivity. We build an assignment model with an endogenous hours choice and complementarities across skills, jobs, and hours. Small gender differences in time available for market work translate into large earnings differences once sorting responds to expected hours, especially in top jobs where the return to hours is high. Calibrated to Current Population Survey data for full time workers from 1980 to 2015, the framework matches key movements in wages and hours and explains a meaningful share of the stalled convergence in gender gaps.
Counterfactuals indicate that lowering the cost of hours for women raises output, and that higher returns to hours amplify both inequality and misallocation. The results point to policies that relax time constraints and weaken convex rewards to time at work, including affordable child care, predictable scheduling, and parental leave that preserves attachment. Further progress toward parity will require changes in the structure of work in addition to continued equalization of skills.

Appendix

Algorithm

- We can now illustrate the algorithm to solve the model. Recall that we have an algorithm to solve (21) and (22) (see Galichon et al. or Bandiera et al. just mentioned). Tha algorithm uses an iterative procedure called Iterative Proportional Fitting (IPFP) to solve:

$$n_x = \mu_{x0} + \sum_y M_{xy}(\mu_{x0}, \mu_{0y}) = \mu_{x0}^F + \sum_y M_{xy}^F(\mu_{x0}, \mu_{0y}) + \mu_{x0}^M + \sum_y M_{xy}^M(\mu_{x0}, \mu_{0y}) \tag{26}$$

$$m_y = \mu_{0y} + \sum_x M_{xy}(\mu_{x0}, \mu_{0y}) = \mu_{0y} + \sum_x M_{xy}^F(\mu_{x0}, \mu_{0y}) + \sum_x M_{xy}^M(\mu_{x0}, \mu_{0y}) \tag{27}$$

where $M_{xy}$is defined in (18).

Code structure

- Start with a guess for the hours distribution for both men and women, $\Pi(h|x^M)^0$, $\Pi(h|x^F)^0$. These are two $\mathcal{H} \times \mathcal{X}$ dimensional matrices, where $\mathcal{H}$is the dimension of the set of the possible hours choices (assume $\mathcal{H}\subseteq[0,1]$ as normalization) and $\mathcal{X}$is the dimension of the set of different skill types (this is identical for men and women).

  Step 1: Solve for the matching functions M_{xy}^M and M_{xy}^F. By the properties mentioned above, an equilibrium exists and is unique.

  To do (for simplicity, I illustrate the procedure for one gender, but this is identical for F and M):

  - Create a function, call it e.g. $marginx$, that - for a given $\mu_{0y}(y)$, computes the model implied mass of total workers n_x according to (25) . Do the analogous for y in (26) (the function will be called $marginy$).
  - Create a function, call it e.g. $marginx_{VEC}$, that takes as input $\mu_{0y}(y)$ and $\mu_{0x}(x)$ and computes the total mass of workers as in (25). Analogously for y in (26) ($marginy_{VEC}$). The difference with the previous function is that the inputs are TWO vectors, $\mu_{x0}(x)$ and $\mu_{0y}(y)$.
  - Using a standard nonlinear solver, write a function (call it $invmargx$) that finds the zero of the (set of) equations:

$$marginx(x, \mu_{x0}, \mu_{0y}(y)) - n_x(x)$$

This basically means, for every skill x, find the number $\mu_{0x}(x)$ that clears the market, for a given vector μ_{0y}. Analogously for y ($invmargy$).

- Now the proper IPFP part.
  * Guess μ^0_{0x},μ^0_{y0}.
  * Compute the new, implied μ^1_{0x},μ^1_{y0} using $invmargx$ and $invmargy$, given μ^0_{0x},μ^0_{y0}.
  * Check that 1) μ^0_{0x},μ^0_{y0} and μ^1_{0x},μ^1_{y0} are sufficiently close and that 2) market clearing at μ^1_{0x},μ^1_{y0} is satisfied (this is when we need $marginx_{VEC}$ and $marginy_{VEC}$)
  * If yes, stop. If no, use μ^1_{0x},μ^1_{y0} as a new guess and repeat.

Step 2: Back out wages w^M_{xy}, w^F_{xy}. Wages are backed out using the fact that, by definition:

$$w = f - V$$

and that

$$V = log\frac{\mu_{xy}}{\mu_{oy}}$$

as in (16).

Step 3: Compute the new, updated guess for the hours distribution $\Pi(h|x^M)^1$, $\Pi(h|x^F)^1$. Now, we have solved for the equilibrium matching and wages. We can then update the hours distribution and compute it using the usual implied probabilities when the shocks are EV type distributed (see equation 24).

Step 4: Stop when $\Pi(h|x^M)^1$, $\Pi(h|x^F)^1$ and $\Pi(h|x^M)^0$, $\Pi(h|x^F)^0$ are sufficiently close. Check that $\Pi(h|x^M)^1$, $\Pi(h|x^F)^1$ and $\Pi(h|x^M)^0$, $\Pi(h|x^F)^0$ are close enough, otherwise repeat steps 1-2-3.

- The algorithm delivers an hours distribution for men and women, a matching probability for men and women, and a wage function for men and women.

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