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June 12, 2024

Re: Jenny Peters, Simposio de la Asociación Española de Economía

TO THE ORGANIZERS THE OF SIMPOSIO

This letter is to confirm that I am the PhD supervisor of Jenny Peters. Jenny started her PhD at the University of Edinburgh in 2021 and is currently in her third year.

Please do not hesitate to contact me if you have any questions.

Yours sincerely,

Maia Guell

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Gender Gaps in the Labour Market: Implications from a Search Model

Jenny Peters

June 13, 2024

Abstract

A growing literature has analysed the persistence of gender differentials in the labour market, modeling the decisions of women explicitly and endogenously. Although women's education levels and labour force attachment have increased significantly, gender gaps in the labour market remain persistent. Motivated by this and the importance of understanding the heterogeneity of labour market outcomes by gender and skill, I develop a three-state search model of the labour market with returns to experience, an endogenous participation margin, and differences in skills. The model builds a multi-outcome framework, providing unified insights into the dynamic interaction of gender gaps in unemployment, labour force participation, labour force entry flows, and labour market experience.

1 Introduction

The persistence of gender differentials in the labour market remains a puzzling fact. Women have achieved significant gains in education and there has been a stark increase in female labour force participation. Despite this, gender differences in the labour market prevail. To shed new light on why gender differentials in the labour market remain so persistent, this paper studies gender differences in a multi-outcome framework, focusing on differences in labour force participation, unemployment rates, entry flows, human capital accumulation, and wages in a dynamic framework.

The first part of the paper is empirical and I document that women are characterized by lower labour force participation, lower tenure, fewer hours of work, and higher hours of home production. This effect is especially pronounced for low-skilled women who also face higher unemployment rates. I also illustrate the importance of considering within-gender differences in labour market outcomes. More low-skilled than high-skilled women are on the participation margin, although they still participate less than high-skilled men. Additionally, differences in non-market hours are larger for low-skilled women, who spend over the equivalent of one working day a week more time on home production than their male counterparts.

The second part of the paper is theoretical and I develop and calibrate a quantitative model to study the empirical outcomes mentioned above, building on the 3-state search model developed by Albanesi and Şahin (2018 [3]). There are multiple sources of heterogeneity in my model which generate different labour market outcomes for men and women at different skill levels.

The first source of heterogeneity is the opportunity cost of employment. This can be seen as the value of home production or the utility of not non-market activities. The distribution of this opportunity cost of employment varies by gender and initial skill level and influences quit and search decisions. Women have a higher average opportunity cost of employment and a higher chance of receiving a new draw of this opportunity cost in the following period. This is designed to capture forces such as child-bearing and -rearing, as well as other caring responsibilities. While there are other ways gender differences can be introduced, it is crucial that the model captures the costs that non-market responsibilities impose on women's labour force participation.

The second and third sources of heterogeneity stem from differences in skill levels. Initial skill level is exogenous and depends on the level of completed education: individuals are either high-skilled or low-skilled. Secondly, there is endogenous human capital accumulation. The evolution of human capital is dependent on the labour market state an agent is in. Human capital is accumulated when employed, and depreciates when unemployed or non-participating. Endogenous human capital and initial skill level determine worker productivity which, in turn, determines wages. It is important that the quantitative theory exhibits wage heterogeneity both between men and women but also among women of different skill levels, as is observed in the data. Here, learning-by-doing explicitly introduces a trade-off between increased utility from substituting market production with home production and the increase in future wages obtained from remaining employed. In this way, returns to experience significantly change agents' labour supply decisions and the wage offered today is not the sole determinant of the return to working.

I argue that women's higher average opportunity cost of employment causes a reduction in time spent working and, hence, less human capital accumulation relative to men. This effect is especially pronounced for low-skilled, low-income women as they have less options to outsource childcare. As a result, career interruptions associated with household care work and/or children can be costly in this model through both the human capital accumulation channel and the participation margin, they are inextricably linked. Thus, this model implicitly includes a life-cycle dimension where persistent and large shocks to the opportunity cost of employment can be used to model motherhood penalties and other barriers to women's labour force participation, and these have a dynamic impact on wages through endogenous human capital accumulation. The model is calibrated to match salient moments in the data. Certain parameters are set based on empirical evidence and the rest are determined to match key data moments.

The contributions I make are both empirical and theoretical, as I illustrate in detail the empirical facts behind differences in female labour market outcomes and then quantify these in a search and matching model. The main finding of this paper is the inextricable link between participation differences, wages and human capital accumulation. Increased labour force participation leads to higher returns from on-the-job learning in terms of productivity and wages, but returns to experience also influence labour force participation rates by making career interruptions more costly. This incentivizes labour force participation, especially in high-skilled occupations with steep wage profiles. Hence, policies aimed at increasing training offered to women may somewhat alleviate gender differences in labour supply. At the same time, the response of low-skilled women's labour supply is more muted as they have less steep wage profiles and fewer opportunities to outsource household production.

The rest of the chapter is organised as follows, the Literature Review places my contribution within the existing literature. Subsequently, the Empirical Facts section features a detailed exposition of the labour market statistics my model aims to explain and gives an empirical justification for the mechanisms I employ. The Model chapter outlines the three-state search model in detail, in Calibration I outline the calibration methodology and results. Finally Quantitative Analysis describes counterfactual experiments carried out and the Conclusion wraps up.

2 Literature Review

This chapter contributes to multiple strands of literature. Firstly, it contributes to literature on the changing labour market outcomes of men and women. This literature focuses on increases in female employment and determinants of gender earnings gaps. The large body of literature examining the convergence of labour market outcomes of men and women focuses on the increase of female labour market attachment (e.g., Azmat et al, 2006 [6]) and female employment rates. These papers find that this change is due to structural transformation (Petrolongo and Ronchi, 2020 [27], Olivetti and Petrolongo, 2014 [25], Olivetti and Ngai, 2015 [24]), increases in marginal returns to experience for women (Olivetti, 2006 [22]), and changes in beliefs about female labour force participation (Fernandez, 2013 [11]). Papers also attribute increased female employment to changes in family policies such as reductions in child care costs, increases in paid parental leave (Sànchez-Marcos and Bethencourt, 2018 [28] Olivetti and Petrolongo, 2018 [26], Goldin et al., 2020 [15]) and factors related to reproductive health such as the introduction of the contraceptive pill or improvements to maternal health. The literature has also established a link between fertility decisions and female labour market outcomes, both unemployment and wages, finding that labour market frictions induce postponed fertility (see, e.g. Da Rocha and Fuster, 2006 [7]).

A large subset of literature on changing labour market outcomes for men and women focuses on gender pay gaps. These papers emphasize the importance of differential human capital accumulation (Erosa et al., 2016 [9]), industry differences ([21]), as well as fertility and home production (Guner et al., 2019 [16], Goldin et al., 2022 [14], Albanesi and Olivetti, 2009 [1]), among other factors. Papers that analyse a wider variety of labour market outcomes, including occupational choice, wages and hours emphasise the significance of gender differences in non-market responsibilities (Erosa et al., 2022 [10]), similar to the narrative offered by Goldin (2014 [13]).

Despite the abundance of literature analysing labour market outcomes of men and women, less research has aimed at explaining changes in labour market outcomes of men and women in unison in a multi-outcome framework. Most papers that do incorporate labour force participation, unemployment rates, entry flows, and gender wage gaps are only able to endogenously match some, but not all, empirical moments. So, for example, many papers do not generate a gender pay gap close to the one found in the data (see, for example, Albanesi and Prados, 2022 [2]). In fact, the majority of papers that generate labour market flows consistent with the data generate negligible gender pay gaps. Albanesi and Şahin (2018 [3]) document the convergence of male and female unemployment rates, but are unable to endogenously generate a gender pay gap as large as the one in the data. They find that the closing of the gender unemployment gap is accounted for by the convergence in male and female labour market attachment. However, they analyse the convergence of overall unemployment rates, while my contribution is linked to an analysis of unemployment rates by skill groups, where this convergence is less clear. According to their paper, there is a positive relationship between the participation gap and the unemployment gap. Stronger female labour force attachment makes women less likely to quit their jobs to non-participation, rather than increasing the duration of unemployment. Despite this comprehensive analysis of labour market flows, their analysis does not generate a gender pay gap close to that observed in the data. As women value home production relatively more than men in their model women have a higher outside option and, hence, the generated gender pay gap is small. In addition, their paper does not explicitly include human capital accumulation and returns to experience. I contribute to this literature by explicitly including on-the-job human capital accumulation and depreciation when non-employed. These have been documented to be crucial factors in explaining gender wage differentials, as well as explicitly affecting the employment decision, and have a dynamic link to participation differences. Amano et al. (2021 [5]), emphasize the importance of human capital dynamics in shaping the life-cycle gender pay gap. They argue that the interaction between fertility-related career interruptions and on-the-job human capital accumulation is linked to wage differences as employers have an incentive to penalize women with lower labour force attachment when skills accumulate fast on the job.

The second strand of literature that this paper contributes to is literature on unemployment dynamics and labour market flows. A large body of early literature focuses on two-state models with no role for participation decisions. However, research has established the importance of the participation margin and of heterogeneity to labour market flows (Elsby et al., 2015 [8]). Garibaldi and Wasmer (2005 [12]) and Krusell et al. (2011 [18]), among others, endogenise the participation margin, however do not allow for heterogeneity by gender and skill. I contribute to this literature from a different angle as I endogenise the participation margin and focus on the dynamic interaction of heterogeneity by gender and skill in order to capture the forces that are important to female labour market outcomes, as emphasised by the first strand of literature. To the best of my knowledge there does not yet exist a paper that explicitly analyses gender differences in a multi-outcome framework, focusing on differences in labour force participation, unemployment rates, entry flows, human capital accumulation, and wages in a dynamic framework.

3 Empirical Facts and Mechanisms

3.1 Empirical Facts

As this model aims to provide a structural counterpart to the empirical literature it is key to first outline the key empirical outcomes of interest in this paper. These are the gender unemployment gap, labour force participation rates, as well as entry flows from non-participation into employment. Finally, the gender pay gap is also of interest, although the model does not explicitly aim to match the data on wage differentials.

Turning attention first to the gender unemployment gap, the left panel of Figure 1 shows the evolution of the overall gender unemployment gap. The difference between male and female unemployment rates has disappeared, except during recessions. In contrast, the right panel of Figure 1 shows this evolution dis-aggregated by skill levels [1]. The unemployment rates for high-skilled men and women are similar, but the unemployment rates for low-skilled workers diverge significantly. Low-skilled women have significantly higher unemployment rates than low-skilled men.

[1] Here, high-skilled individuals are those with at least a college degree, while low-skilled individuals are those with less than a completed college degree.

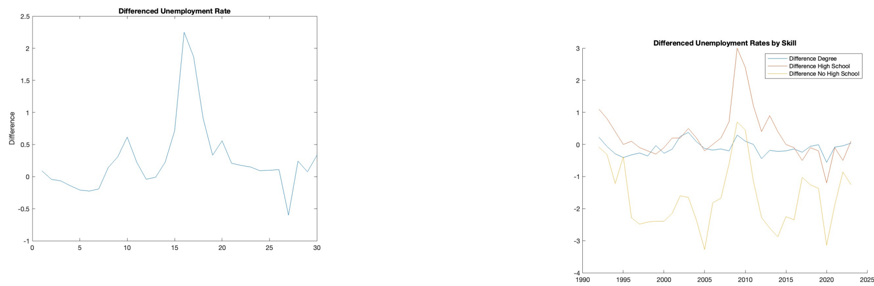

Figure 1: Left Panel: The Gender Unemployment Gap (Yearly). Right Panel: The Gender Unemployment Gap by skill level (Yearly). Source: Own calculations based on CPS data.

Moving to labour market flows, it is visible from 2 that men are more attached to the labour force. High-skilled men flow mostly from employment to employment (EE) or flow into employment from non-participation (NE) or remain in unemployment (UU). Low-skilled men flow mostly from employment into unemployment (EU), from unemployment into employment (UE) and from unemployment to unemployment (UU). High skilled women's labour market flows principally involve employment to employment and entry and exit (EE, NE, and EN) flows. Low-skilled women primarily remain non-participating (NN) and move from unemployment and employment into non-participation (UN and EN). Hence, especially low-skilled women move out of the labour force frequently. Their male counterparts, in comparison, move between employment and unemployment, leaving the labour force for non-participation less. Looking at high-skilled individuals, the picture is similar. High-skilled women are on the participation margin more than their male counterparts. Hence, less men, be they low- or high-skilled, enter and exit the labour market. At the same time, more low-skilled women than high-skilled women move from employment into unemployment and low-skilled women are more present in labour market flows involving unemployment than their high-skilled counterparts. This shows that, by gender, participation differences are the principal distinguishing factor, whereas within gender, differences in unemployment flows play a large role.

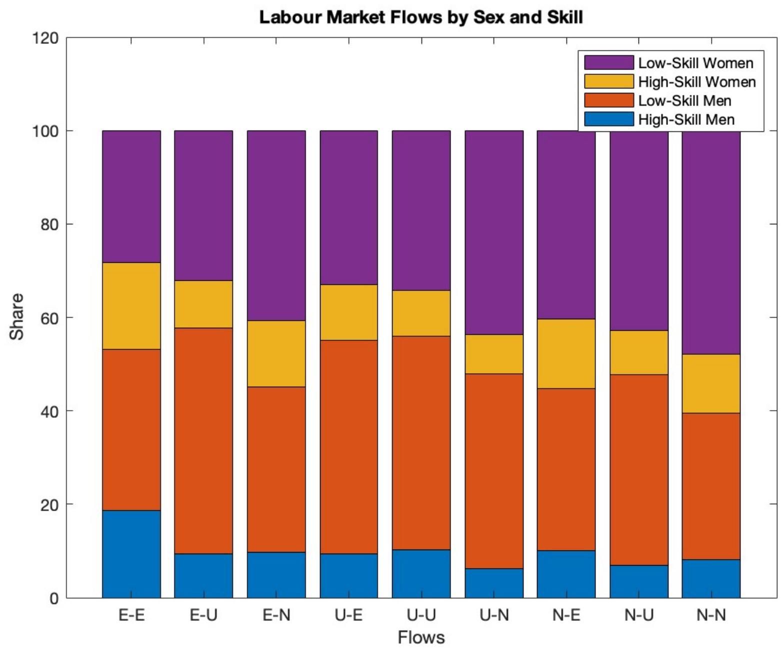

Figure 2: Labour Market Flows by Educational Attainment. Source: Own calculations based on CPS data.

Furthermore, looking at differences in labour force participation rates, the evolution of the labour force participation rate by gender in the left panel of Figure 3 shows that there has been an increase in the LFP of women and a decrease in that of men. However, men still participate more in the labour force than women. The right panel sheds more detail on this by educational attainment. High-skilled women have a higher participation rate than their low-skilled counterparts. Although high-skilled women participate more than low-skilled men, they still participate less than high-skilled men. Similar to previously, there is a within-difference both between men and women and high- and low-skilled individuals. Conditional on skill, women have lower rates of labour force participation than men. Taken together with the previous empirical facts on labour market flows, it becomes clear that women, especially low-skilled women, are less attached to the labour force and are on the participation margin more.

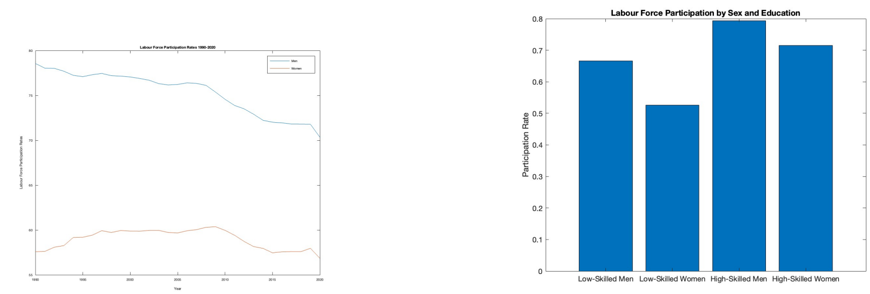

Figure 3: Left Panel: Evolution of Labour Force Participation Rates. Source: US Bureau of Labour Force Statistics. Right Panel: Labour Force Participation Rates by Sex and Education, 2019. Source: Own calculations based on CPS data.

Moving to the evolution of the gender pay gap, the left panel of figure 4 shows that this has been decreasing. The right panel of figure 4 shows the gender pay gap disaggregated by skill level.. Interestingly, for those with below degree-level education, the gender pay gap is larger than for the group of workers with at least a degree. The gender pay gap also varies by skill level. Similarly to the pattern of unemployment rates, the gender pay gap is highest for low-skilled individuals.

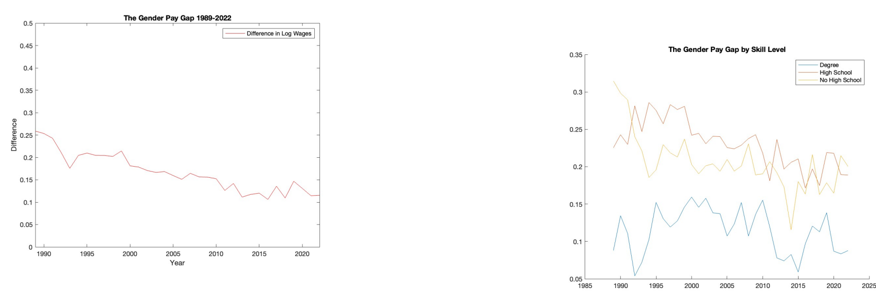

Figure 4: Left Panel: The Gender Pay Gap (Yearly). Right Panel: The Gender Pay Gap by skill level (Yearly). Source:

These empirical facts imply that gender differences in the labour market manifest themselves along multiple dimensions. Gender gaps in unemployment, labour market flows, labour force participation, and wages remain salient features of the US economy. What is more, there are not only differences between the genders, but also within-gender differences conditional on educational attainment. Low-skilled women have higher unemployment rates and are less attached to the labour force than high-skilled women and men. Hence, significant gender differences previously unaccounted for remain.

3.2 Model Mechanisms

The model uses two main mechanisms to generate the above empirical findings: On-the-job human capital accumulation and differences in the opportunity cost of working. This section gives an empirical foundation to the relevance of each of these mechanisms in turn.

3.2.1 Human Capital Accumulation

Firstly, the importance of including differences in on-the-job human capital accumulation in a dynamic framework to explain gender differences in the labour market can be seen from figure 5 where tenure, or time spent with the same employer, is taken as a proxy for labour market experience. Tenure is substantially different between low- and high-skilled men and women. As the left panel of figure 5 shows, high-skilled men and women have similar tenures and women surpass men from 55 years of age onwards. However, the right panel of figure 5 shows that low-skilled men have considerable more years with the same employer than their female counterparts. Men tend to have more labour market experience, but this discrepancy is more pronounced for low-skilled individuals than high-skilled workers. This points to the fact that low-skilled women are less attached to their employers. This may be due to the fact that they are less attached to the labour force or their jobs are less stable, or both. If certain skills are specific to the employer an individual works for, higher turnover means that low-skilled women have less opportunities to acquire this employer-specific human capital.

Figure 5: Left Panel: Years with the same employer, high skill. Right Panel: Years with the same employer, low skill. Source: BLS.

Furthermore, as can be seen from figure 6, men spend considerably more average hours at work a week than women, independent of skill levels. At the same time, high-skilled individuals spend more time at work than their low-skilled counterparts. The gender-skill group that spends the least time at work is low-skilled women. Figure 5 and 6 imply that women, especially low-skilled women, have less opportunities to accumulate human capital through on-the-job learning-by-doing, as they spend less hours working in general and also less years with the same employer.

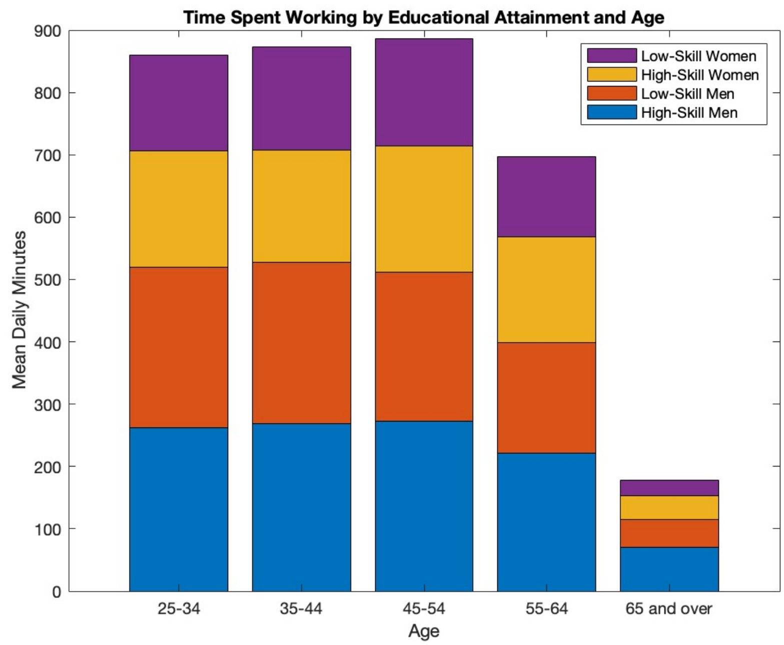

Figure 6: Hours at Work by Educational Attainment and Sex. Source: Own calculations based on ATUS data.

3.2.2 Opportunity Cost

The second mechanism employed in this model is differential opportunity cost of working, or differential values placed on home production. To illustrate the relevance of this mechanism, an illustration of the division of household tasks is necessary. Figure 7 breaks down time spent on household tasks by educational attainment, sex, and age. The left panel of figure 7 shows the mean daily minutes spent on household chores. Women spend more time than men on household chores, but this difference is most pronounced for low-skilled individuals. Averaging throughout different age groups, low-skilled women spend about 9 hours a week more on household chores, while high-skilled women spend on average 7 hours a week more. This is equivalent to a whole work day that women spend on non-market production relative to their male counterparts. The right panel of 7 shows the mean daily minutes spent on household care, both caring for children and adults in the household. Women spend about 2 hours a week more

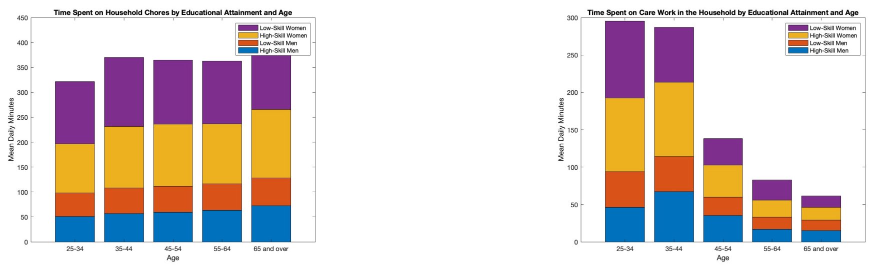

Figure 7: Left Panel: Time Spent on Chores by Educational Attainment and Sex. Right Panel: Time Spent on Care in the Household, Source: Own calculations based on ATUS data.

than men caring for household members. Except for the youngest age cohort, high-skilled women spend more time on household care than their low-skilled and, hence, spend more time on childcare at a younger age.

Taking both of these together, women spend more time on non-market responsibilities than men, be they household chores or time devoted to caring for fellow household members. Women spend on average about 20 hours a week on non-market responsibilities, although high-skilled women spend relatively less time on household chores and more on childcare. This may be because high-skilled high-income women can more easily outsource chores, whereas childcare remains in the household. In contrast to that, men spend on average 10 hours, half the time that women do, on non-market responsibilities. These gender asymmetries in time use translate into asymmetries in time devoted to market production, which was visible in the previous section. This, in turn translates into asymmetries in labour market outcomes. In the model this discrepancy is illustrated through women having a higher and more dispersed opportunity cost of working.

Hence, although there is a myriad of ways gender differences can be introduced in a model, my empirically-driven approach is to assume that the presence of children and other non-market responsibilities involve a forced reduction in the hours of market work that falls predominantly on females. Female workers are characterized by higher unemployment, higher flows to non-participation, lower labour market attachment, and fewer hours of market work. These gender differences imply that women accumulate less labour market experience and, hence, less human capital, than men. Differences in labour force attachment and in expected future labour supply may also lead to lower incentives to invest in human capital.

4 Model

4.1 Set-up

The model is based on the search and matching model developed by Albanesi and Sahin, mostly based on Pissarides (2000). A critical component of the hypothesis of this chapter is the link between gender gaps in labour market participation, unemployment, and experience. Therefore, the model includes an explicit participation decision and on-the-job human capital accumulation. Hours of work are fixed and wages are determined by surplus splitting between workers and firms in each skill group.

Before a match can be formed, firms must post a vacancy, then a firm and a worker meet and job creation takes place. The number of jobs is endogenously determined by profit maximisation and each firm is small and has one vacancy. There is free entry and a matching function following Pissarides (2000) determines job finding prospects of each worker.

4.2 Workers

The economy is populated by a continuum of unit measure of workers of different gender, $j = f, m$ and skill, $i = nc, c$, where c denotes high-skill (college) workers and nc low skill (non-college).

Each worker is either employed, unemployed or non-participating (out of the labour force). In addition to initial skill level, the model includes dynamic human capital accumulation. Consistent with a view of "learning-by-doing" human capital accumulation, workers may accumulate their human capital when employed. When unemployed or out of the labour force, human capital depreciates each period. The evolution of human capital affects each worker's productivity, y, but $y_{nc,k} \leq y_{c,k}$ - high skilled workers are at least as productive as low skilled workers, regardless of how much human capital has accumulated on the job or depreciated when non-employed.

In addition to initial skill level and dynamic human capital, each worker is characterized by their realisation of the opportunity cost, x. Men and women in the model have a differential opportunity cost of being in the labour force, designed to reflect the gender-specific differences outlined in the previous chapter. It can be interpreted as the value of home production and is stochastic and conditionally i.i.d. over time. This individual opportunity cost influences quit and search decisions, and individuals may receive a new draw of their opportunity cost of working with a probability that also varies by gender.

The main assumption of this model is that women's opportunity cost of working is higher on average and that women have a higher probability of drawing a new value of this cost. Given that the opportunity cost is a proxy for the value of home production, this assumption is intended to capture the extent of gender differences in labour supply that has been widely documented in the literature. The cumulative distribution function of x is represented by $F_{i,j}(x)$. At the beginning of each period, each agent draws a value of x, denoted by x', and may receive a new draw each period with probability $\lambda_{i,j} \in [0, 1]$. The distribution of x also varies by skill and gender to capture different opportunity costs depending on educational attainment. High-skilled women, for example, may have a lower opportunity cost of working than their low-skilled counterparts, either because they have sufficient income to outsource household chores or because they have more relative bargaining power within the household.

Additionally, before the agent can make any decisions, they may receive an exogenous separation shock, $\delta_{i,j} \in (0, 1)$, if employed, or a job offer with probability $p_i \in [0, 1]$ if unemployed. Then, depending on the opportunity cost, x, and the current labour market state, workers may make decisions to change labour market states or remain in their current labour market state.

The flow values of each worker of type i, j depend on the realised value of x, their human capital k, and labour market status:

$$v^E_{i,j}(x, k, w) = w + \frac{(\overline{T} - h)}{\overline{T}} x \tag{1a}$$

$$v^U_{i,j}(x, k) = \frac{(\overline{T} - s)}{\overline{T}} x \tag{1b}$$

$$v^N_{i,j}(x, k) = x \tag{1c}$$

Equation (1a) denotes the flow value of an employed individual with individual opportunity cost x, where h is the time devoted to market work, which is fixed, and $(\overline{T} - h)/\overline{T} \in (0, 1]$ the fraction of total active hours available for home production. Equation (1b) is the flow value of an unemployed individual, where s is the time spent searching for a job and $(\overline{T} - s)/\overline{T} \in [0, 1]$ the fraction of time spent on home production. The flow value of non-participation is given by (1c), non-participants receive the utility value of home production/the opportunity cost of employment.

Given this set-up and the assumptions on timing, workers' value functions are as follows. For employed individuals:

$$
\begin{aligned}
V^E_{i,j}(x,k,w) = {} & v^E_{i,j}(x,k,w) + \lambda_{i,j}\beta \\
& \int_{\underline{x_{i,j}}}^{\overline{x_{i,j}}} \Big[(1-\delta_{i,j}) max\{V^E_{i,j}(x',k',w), V^U_{i,j}(x',k',w), V^N_{i,j'}(x',k',w)\}\Big] dF_{i,j}(x') \\
& + \lambda_{i,j}\beta \int_{\underline{x_{i,j}}}^{\overline{x_{i,j}}} \Big[\delta_{ij} max\{V^U_{i,j}(x',k',w), V^N_{i,j}(x',k',w)\}\Big] dF_{i,j}(x') \\
& + (1-\lambda_{i,j})\beta \Big[(1-\delta_{i,j}) V^E_{i,j}(x,k',w) \\
& + \delta_{i,j} max\{V^U_{i,j}(x,k',w), V^N_{i,j}(x,k',w)\}\Big]
\end{aligned} \tag{2}
$$

where $i = nc, c$ and $j = m, f$ and β is the discount factor and $\underline{x_{i,j}}$ and $\overline{x_{i,j}}$ are the extremes of the support of the distribution of x. Equation (2) shows that an agent who receives a new draw of the opportunity cost, labeled as x', with a probability $\lambda_{i,j}$ and does not receive a separation shock can decide whether to stay employed or quit to unemployment or non-participation, depending on their realised opportunity cost. Additionally, that agent's human capital accumulate to k'. If that individual receives a separation shock, they can choose between unemployment or non-participation, but can still accumulate human capital. If, with chance $1 - \lambda_{i,j}$, the agent's opportunity cost remains the same, they will choose to remain in their current state if they do not receive a separation shock, and their human capital accumulates. If they do receive a separation shock, they may again choose between unemployment or non-participation, and their human capital accumulates.

For unemployed individuals:

$$
\begin{aligned}
V^U_{i,j}(x,k,w) = {} & v^U_{i,j}(x,k) + \lambda_{ij}\beta \\
& \int_{\underline{x_{i,j}}}^{\overline{x_{i,j}}} \Big[p_i max\{V^E_{i,j}(x',k',w), V^U_{i,j}(x',k',w), V^N_{i,j}(x',k',w)\}\Big] dF_{i,j}(x') \\
& + \lambda_{ij}\beta \int_{\underline{x_{i,j}}}^{\overline{x_{i,j}}} \Big[(1-p_i) max\{V^U_{i,j}(x',k',w), V^N_{i,j}(x',k',w)\}\Big] dF_{i,j}(x') \\
& + (1-\lambda_{ij})\beta \Big[p_i max\{V^E_{i,j}(x,k',w), V^U_{i,j}(x,k',w)\} \\
& + (1-p_i) V^U_{i,j}(x,k',w)\}\Big]
\end{aligned} \tag{3}
$$

An unemployed worker who draws a new value of the opportunity cost, x' and receives a job offer with probability p_i may decide between taking the job, staying unemployed or moving to non-participation. If the individual does not receive a job offer, they can only decide between unemployment or exiting the labour force. In either case, their human capital depreciates to k'. If the unemployed worker does not receive a new draw of the opportunity cost, they will remain unemployed, unless they receive a job offer, in which case they will choose between employment and unemployment, depending on the realised value of their opportunity cost. Again, in both cases the agent's human capital depreciates.

For individuals out of the labour force:

$$
\begin{aligned}
V^N_{i,j}(x,k,w) = {} & v^N_{i,j}(x,k) \\
& + \lambda_{ij}\beta \int_{\underline{x_{i,j}}}^{\overline{x_{i,j}}} \Big[max\{V^U_{i,j}(x',k',w), V^N_{i,j}(x',k',w)\}\Big] dF_{i,j}(x') \\
& + (1-\lambda_{ij})\beta V^N_{i,j}(x,k',w)
\end{aligned} \tag{4}
$$

Equation (3) shows that a non-participant who receives a new draw of the opportunity cost may choose to stay out of the labour force or start searching for a job, hence becoming unemployed. If they do not receive a new draw of the opportunity cost they will remain non-participating. Additionally, that individual's human capital depreciates.

4.3 Firms

Production is carried out by a continuum of unit measure of firms using labour as the only input and there is free entry in the firm sector. A firm can hire one worker only and there are separate job markets for each exogenous skill group. Within the two skill groups, workers' productivity depends on accumulated human capital, which affects productivity and, hence, wages. Within each skill group, wages are chosen to split the surplus between firm and worker. Firms do not observe the worker's individual opportunity cost, but they do know the distribution of characteristics in the pool of currently unemployed workers.

The value of a filled job at wage w:

$$
\begin{aligned}
J_{i,j}(w,k) = {} & y_i(k) - w_{i,j,k} \\
& + \beta \Big[\int_{\underline{x_{i,j}}}^{min\{x^q_{ij}(w), x^a_{ij}(w)\}} (1-\delta_{i,j})(J'_{i,j}(w,k) + \delta_{i,j}V_i) dF_{i,j}(x') \\
& + \int_{min\{x^q_{ij}(w), x^a_{ij}(w)\}}^{\overline{x_{i,j}}} V_i dF_{i,j}(x') \Big]
\end{aligned} \tag{5}
$$

Equation 5 shows that the value of a filled job depends on the flow value (productivity, a function of human capital, less the wage) and on whether the worker quits or the job is exogenously destroyed. If the job is not exogenously destroyed and the worker's opportunity cost is low enough, they will stay at the firm. If the job is destroyed exogenously, the firm creates a new vacancy with value V_i. Even if the job is not exogenously destroyed, the worker may still quit if their opportunity cost is too high, in which case the firm will again create a vacancy with value V_i.

4.4 Wage Setting

Firms offer a wage conditional on observable characteristics based on their assessment of the characteristics of currently unemployed workers. The individual opportunity cost of working is not observed but firms know the distribution of characteristics in the pool of currently unemployed workers. Initial skill level and human capital are observed.

Let $w_{i,j,k}$ denote the equilibrium wage based on which people chose to be in the labour force given their value and policy functions. Firms will then choose a wage $\hat{w}$ to solve the surplus splitting problem:

$$w_{i,j,k} = argmax_{\hat{w}} \Bigg[\int_{\underline{x_{i,j}}}^{min\{x^a_{i,j}(w_{i,j,k}), x^q_{i,j}(w_{i,j,k})\}} max\{0, V^E_{i,j}(x,k,\hat{w}) - max\{V^U_{i,j}(x,k,\hat{w}), V^N_{i,j}(x,k,\hat{w})\}\} dF_{i,j}(x) \Bigg]^{\gamma} x \Bigg[J_{i,j}(\hat{w_k}) Q_{i,j}(\hat{w_k}, w_{i,j,k}) - V_i \Bigg]^{1-\gamma} \tag{6}$$

where

$$Q(\hat{w_{ij}}, w_{ij}) = \frac{\int_{\underline{x_{i,j}}}^{min\{x^a_{ij}(\hat{w_{ij}}), x^q_{ij}(\hat{w_{ij}})\}} dF_{i,j}(x)}{\int_{\underline{x_{i,j}}}^{min\{x^a_{ij}(w_j), x^q_{ij}(w_j)\}} dF_{i,j}(x)}$$

for $j = f, m$. Here, $0 \leq \gamma < 1$ is the worker's bargaining power, $V^E_{i,j}(x, k\hat{w}) - max\{V^U_{i,j}(x,k,\hat{w}), V^N_{i,j}(x,k,\hat{w})\}$ is the worker's surplus and $J_{i,j}(\hat{w_k})Q_{i,j}(\hat{w_k}, w_{i,j,k}) - V_i$ the firm surplus. The fraction $Q(\hat{w_{ij}}, w_{ij})$ represents the fraction of workers of type i, j, k who would be willing to work at wage $w_{i,j,k}$ and would also be willing to work at the wage $w_{\hat{i,j},k}$. This fraction essentially denotes that the firm is aware that by reducing the candidate wage they also reduce the pool of available employees. Additionally, the firm also understands that, conditional on accepting the job at a lower wage, workers are also more likely to quit. The fixed point of this policy function constitutes an equilibrium wage.

The Appendix describes the stationary equilibrium characterization in detail.

5 Calibration

In this section I discuss the calibration results from the Simulated Method of Moments (SMM), including initially chosen parameters, calibrated parameters and evaluate the performance of the model for targeted and non-targeted moments.

I calibrate the model in a two-step procedure. Firstly, I take a set of parameters from the data and the literature without estimating the model. These parameters include the initial skill distribution by gender and parameters linked to the law of motion for human capital. Secondly, the set of calibrated parameters is chosen by targeting a set of salient data moments linked to female labour force participation, unemployment rates, and flows from non-participation. To match the data moments of interest, I choose SMM.

5.1 Exogenous Parameters

Initial Skill Distribution by Sex. To match the initial skill distribution by sex I use data from the US Current Population Survey (CPS), a monthly survey from the US Bureau of Labour Statistics (BLS). I target workers older than 25 years. Individuals with less than a college degree are distinguished from individuals with at least a college degree (low-skilled versus high-skilled). I set the educational composition of the labour force by sex to their empirical values in 2019 (see Table 1).

	Skilled	Unskilled
Men	0.202	0.330
Women	0.211	0.258

Table 1: Exogenous Initial Skill Distribution

Law of Motion for Human Capital. I use the the law of motion for human capital estimated by Olivetti (2006) [23], where human capital in the next period depends on previous human capital and employment status in the current period. That is,

$$k(\theta_i, h) = (1 - \delta_k)\theta_i + h^{\psi} \tag{7}$$

where θ_i is the stock of human capital of an individual of initial skill level $i \in \{nc, c\}$, δ_k the human capital depreciation rate, h hours worked a day and ψ the learning rate. Olivetti adjusts for sample selection and obtains bias-corrected estimates for δ_k and ψ. In particular, $\delta_k = 0.2$ and $\psi = 0.4$.

Time Allocated to Working/Job Search. I assume that the fraction of time allocated to working, h, is 10 hours out of 16 active hours. The fraction of time allocated to working is then $\frac{10}{16} = 0.625$ and the time available for home-production $\frac{(\overline{T}-h)}{\overline{T}} = 0.375$. In a similar fashion, I set the time spent searching for a job, s, to 2 hours out of 16 active hours (as reported in Krueger and Mueller, 2011 [17]). The fraction of time spent searching for a job is then $\frac{2}{16} = 0.125$ and the time available for home production $\frac{(\overline{T}-s)}{\overline{T}} = 0.875$.

Matching and Vacancies. I assume the matching function is Cobb-Douglas and set the elasticity of the matching function, $m(u, v) = \mu u^{\alpha} v^{1-\alpha}$, with respect to unemployment (α) following Shimer (2005 [29]). I set workers' bargaining power, γ, equal to the elasticity of the matching function with respect to unemployment. Finally, I set the vacancy creation cost parameter equal to about three months of earnings, 8.5.

Discount Factor. I interpret the model as monthly and use $\beta = 0.96$ (following Kydland and Prescott, 1982 [19]).

5.2 Calibrated Parameters

The remaining parameters are set to match the targeted moments: labour force participation rates by skill and gender, unemployment rates by skill and gender, NE flows by skill and gender. These 12 moments are calibrated using the following 9 parameters: κ_{ij}, $\overline{x}_{if}$, λ_{ij} (See Table 2) . Here, κ_{ij} is the tail parameter of the Pareto distribution of the opportunity cost by initial skill and sex and $\overline{x}_f$ is the upper bound for the support of the opportunity cost in the discretized distribution. λ affects the frequency in chances to agents' work attitudes while x affects their value of being in the labour force. These parameters jointly determine the value of employment, unemployment, and non-participation, hence determining employment and labour force participation decisions. The average duration for shocks, governed by λ are as are follows: 10 years for low-skilled men, 5 years for low-skilled women, 8 years for high-skilled men and only 1.5 years for high-skilled women. The chance of receiving a new draw of the opportunity cost is significantly lower for men, as shocks represent, e.g. childcare responsibilities and other caring responsibilities or childbirth/pregnancy. To match labour force participation and unemployment rates, it must be the case that the opportunity cost shocks of high-skilled women are less persistent than for any other group considered in the model. This may be because high-skilled women can more easily outsource household work and, hence, after receiving a high value of x receive a lower value relatively faster than low-skilled women.

Parameter	Description	Value
$\kappa_{nc,m}$	Shape parameter of distribution of opportunity cost of low-skilled men.	9.328
$\kappa_{c,m}$	Shape parameter of distribution of opportunity cost of skilled men.	20.456
$\kappa_{nc,f}$	Shape parameter of distribution of opportunity cost of low-skilled women.	78.812
$\kappa_{c,f}$	Shape parameter of distribution of opportunity cost of skilled men.	17.107
$\overline{x}_f$	Extreme of the support of the opportunity cost of women.	9.622
$\lambda_{nc,m}$	Arrival rate of x shock for low-skilled men.	0.008
$\lambda_{c,m}$	Arrival rate of x shock for skilled men.	0.016
$\lambda_{nc,f}$	Arrival rate of x shock for low-skilled women.	0.010
$\lambda_{c,f}$	Arrival rate of x shock for skilled women.	0.055

Table 2: Parameters Calibrated with SMM.

Figure 8 gives a graphical representation of the diustribution of the opportunity cost by gender and initial skill level.

Figure 8: Left Panel: Cumulative distribution function of the opportunity cost by gender and skill. Right Panel: Calibrated distribution of the opportunity cost by gender and skill level.

Additionally, I correct for misclassification in labour market flows by introducing the misclassification probabilities estimated by Abowd and Zellner (1985 [20]) to mitigate the problem of measurement error in labour market flows. They estimate a transition matrix in order to control for this well-known problem in three-state search-matching models (see the Appendix).

5.3 Evaluation: Targeted Moments

Table 3 shows the model outcomes versus the data targets. In general, I am able to reproduce the data targets closely. In particular, the model performs well in matching female labour force participation rates and flows from non-participation to employment for women. I fall slightly short on the moments relating to male labour market outcomes. Most importantly, the model-generated labour force participation rate for low-skilled men is much smaller than that found in the data. In general, the model matches the data well for skilled individuals and less so for low-skilled individuals.

		Model	Data
Male LFP	Unskilled	0.399	0.667
	Skilled	0.887	0.794
Female LFP	Unskilled	0.486	0.526
	Skilled	0.754	0.715
Male Unemployment Rates	Unskilled	9.76 %	7.96%
	Skilled	2.10%	3.29%
Female Unemployment Rates	Unskilled	6.82 %	7.69%
	Skilled	5.49%	3.45%
NE Flows - Men	Unskilled	0.011	0.049
	Skilled	0.060	0.055
NE Flows - Women	Unskilled	0.019	0.039
	Skilled	0.054	0.054

Table 3: Targeted Moments: Model vs Data.

5.4 Evaluation: Non-Targeted Moments

Here I discuss the model's results for selected non-targeted moments that are relevant to male-female labour market differentials. The first set of relevant non-targeted moments are labour market flows for skilled individuals. As Table 4 shows, the model manages to reproduce quite well the labour market flows for skilled women. For skilled men, the model somewhat underpredicts EN and UN flows relative to the data.

	Skilled Women				Skilled Men		
Data	E	U	N		E	U	N
E	0.968	0.008	0.029	E	0.977	0.007	0.020
U	0.287	0.559	0.235	U	0.239	0.619	0.182
N	0.054	0.019	0.908	N	0.055	0.022	0.901
Model							
E	0.964	0.007	0.03	E	0.984	0.008	0.009
U	0.305	0.588	0.107	U	0.399	0.529	0.073
N	0.054	0.049	0.897	N	0.060	0.019	0.921

Table 4: Non-Targeted Moments Labour Market Flows for Skilled Workers: Model vs Data.

The second set of relevant non-targeted moments are the labour market flows for low-skilled individuals. As is visible from Table 5, the model falls short on producing the same magnitude of EU and EN flows for low-skilled women. The model-generated flows are too low in comparison to the data. In general, the model is better able to match flows for low-skilled men than women.

	Low-Skilled Women				Low-Skilled Men		
Data	E	U	N		E	U	N
E	0.944	0.016	0.054	E	0.952	0.019	0.039
U	0.537	0.537	0.332	U	0.239	0.567	0.253
N	0.039	0.023	0.916	N	0.049	0.033	0.889
Model							
E	0.965	0.006	0.028	E	0.962	0.015	0.023
U	0.182	0.681	0.136	U	0.174	0.698	0.129
N	0.019	0.015	0.966	N	0.011	0.011	0.978

Table 5: Non-Targeted Moments Labour Market Flows for Low-Skilled Workers: Model vs Data.

Finally, another relevant set of non-targeted moments are gender pay gaps by skill level. It is well-known that quantitative macro labour models usually fall short in generating a gender pay gap of the same magnitude as the one found in the data. The model is unable to generate a gender pay gap for unskilled individuals, it is 31% in the data, but there is no low-skilled gender pay gap in the model. For skilled individuals, the model is only able to capture about one third of the gender pay gap found in the data. This shows that returns to experience, heterogeneity in initial skills and differential utilities of home production are not enough to account for the earnings inequality in the data.

	Model	Data
Unskilled	1.00	1.31
Skilled	1.088	1.27

Table 6: Non-Targeted Moments Gender Pay Gaps: Model vs Data.

5.5 Discussion

Overall, the model manages to replicate the direction and magnitude of most targeted and non-targeted moments to a satisfactory degree. The model falls short on adequately capturing the magnitude of the gender pay gaps by skill level. In this model, the gender pay gap arises due to two interrelated mechanisms. Firstly, as women are more likely to quit because they have a higher opportunity cost, the value of a match with a female worker is lowered. This is especially the case for high skilled workers as the foregone surplus is larger. Secondly, given women's higher quit rates, they have less time to accumulate human capital on the job and, hence, are on average less productive. It is likely that various other factors not captured by the model contribute to the gender pay gap found in the data. At the same time, however, given that women have a higher opportunity cost they also have a higher outside option, leading them to require higher wages than men to work. These two factors counteract one another and may lead to muted response of the gender pay gap.

6 Quantitative Analysis

An advantage of a structural model is that I am able to perform quantitative experiments to gauge the relevance of individual mechanisms employed in the model.

6.1 Parameters governing the Human Capital Process

The first experiment I carry out is varying the parameters governing the human capital accumulation process (different depreciation and learning rates) by gender and skill. Previously, I abstracted from gender differences but, in practice, gender discrimination in C-Suite positions (Albanesi et al., 2015 [4]) may reduce the rate of accumulation and increase depreciation for skilled women. Additionally, spells of non-participation may not only lead women to accumulate less human capital on the job, but may even increase depreciation rates for women relative to men if these depreciation rates are proportionate to the time spent out of the labour force. Albanesi and Prados (2022 [2]) also document that they fall short of matching gender pay gaps due to abstracting from gender differences in the human capital accumulation process. What is more, it is possible that the learning rate for high skilled individuals is much higher than for low-skilled individuals, perhaps because of a steeper wage profile, i.e. the

		Model	Data
Male LFP	Unskilled	0.518	0.667
	Skilled	0.981	0.794
Female LFP	Unskilled	0.481	0.526
	Skilled	0.802	0.715
Male Unemployment Rates	Unskilled	8.55 %	7.96%
	Skilled	1.54%	3.29%
Female Unemployment Rates	Unskilled	6.54 %	7.69%
	Skilled	4.23%	3.45%
NE Flows - Men	Unskilled	0.014	0.049
	Skilled	0.366	0.055
NE Flows - Women	Unskilled	0.019	0.039
	Skilled	0.069	0.054

Table 7: Differential Human Capital Process: Model vs Data.

derivative of the wage with respect to human capital is high. At the same time, depreciation rates for low-skilled workers may be lower and they may have a less steep wage profile as menial jobs involve less specialization.

In this specification, I set the learning rate for low-skilled women equal to that of low-skilled men (below the rates for high-skilled workers) and set the depreciation rate for low-skilled women higher than that of low-skilled men and the depreciation rate for high-skilled women higher than that of high-skilled men. This specification exacerbates the effect of the dynamic interaction of human capital accumulation and differential opportunity costs.

Focusing only on the previously targeted moments, Table 7 shows the response to differentials human capital processes by skill and gender.

The first difference is a higher labour force participation rate for men and skilled women. Given that depreciation rates for men are quite high in this specification, this increases the trade-off that men face between employment and non-employment. This is mirrored by a reduction in unemployment rates for men, they are less likely to quit endogenously as they now face a higher penalty via the human capital channel. The response of high-skilled women's unemployment rates is similar. For both men and women, the response of entry (NE) flows is quite muted. This makes sense in this specification as the opportunity cost distribution remains unchanged. Hence, keeping constant opportunity cost, this shows that dynamic human capital accumulation affects labour force participation and unemployment rates. An implication for this is that if the goal of policy is to increase labour force attachment and reduce unemployment, training on the job is essential. Even with a relatively high opportunity cost of working, the trade-off between a reduction in future wages via the human capital accumulation channel creates an incentive to remain in the labour force.

7 Conclusion

This chapter studies the interaction of differential labour force trajectories by gender and skill and the role of on-the-job human capital accumulation in determining a range of gender gaps. While most of these gender gaps have been studied individually, this paper creates a multi-outcome framework to gauge the importance of differential opportunity cost and on-the-job human capital accumulation on each of the gender differences in the labour market. I find that dynamic human capital accumulation creates incentives for increased labour force participation, especially for men and high-skilled women. This channel changes the nature of agents' labour supply decisions even when the opportunity cost of working remains constant.

I develop a search and matching model with a participation margin, returns to experience, and differences in skills to explicitly and endogenously model the choices faced by individuals of different gender and skill. My paper contributes to the literature on the different and changing labour market outcomes of men and women but also to a broader literature on unemployment dynamics and labour market flows. The first key contribution is that this model delivers a quantitative framework to analyse the career costs of non-market production, both directly through the participation margin, as well as indirectly through the human capital channel. Secondly, as agents are able to adjust their labour force participation decision each period, this model delivers a dynamic analysis of how factors relating to home production affect labour market outcomes for men and women of different skill levels. Finally, the model offers an excellent framework to address different policies, such as an increase in on-the-job training, on labour force participation rates and unemployment.

There are certain caveats that should be noted. Firstly, the model only considers individuals, rather than households. Decisions regarding childcare and labour supply are likely to be made jointly with the partner, pointing to the importance of including the household and bargaining within the household. Secondly, this model abstracts from the life-cycle dimension, which is especially relevant for fertility. Children are born relatively early in the life-cycle, while the career costs for women may remain persistent throughout middle and older age. Nevertheless, my model aims to implicitly capture the life-cycle dimension through shocks to the opportunity cost which can persist for several model periods. Abstracting from life cycle dynamics is an appropriate first step to best isolate the key mechanisms at play. Finally, the model is not able to fully capture the magnitude of the existing gender pay gap. This is likely because there are some features that the model abstracts from. However, the conclusions regarding the factors affecting labour force participation remain valid.

Further research may include explicitly modelling participation decisions, intra-household bargaining, and endogenous fertility within a life-cycle model.

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A Appendix

A.1 Policy Functions and Worker Flows

Worker's optimal policies are defined by cut-off rules that depend on the opportunity cost, x'. A worker with opportunity cost of working x' and human capital h has the following threshold values of opportunity cost:
They will prefer employment over unemployment if: $x' \leq x^a_{i,j,h}(w)$ and prefer unemployment over employment if: $x' > x^a_{i,j,h}(w)$. If $x' \leq x^q_{i,j,h}(w)$ the worker

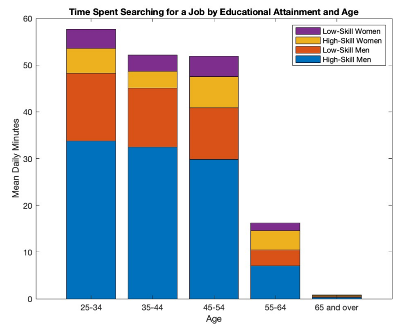

Figure 9: Enter Caption

will prefer employment over non-participation and prefer non-participation to employment if $x' > x^q_{i,j,h}(w)$. Finally, they will choose unemployment over non-participation if $x' \leq x^n_{i,j,h}(w)$ and non-participation over unemployment if: $x' > x^n_{i,j,h}(w)$. These threshold levels depend on the wage as this determines the value of employment.

A.2 Solution and Equilibrium

There are no aggregate shocks so stationary equilibrium is characterized by the following conditions:

- Worker value functions $V^E_{i,j,h}(x;w), V^U_{i,j,h}(x;w)V^N_{ij}(x;w)$ and policy functions $x^a_{i,j,h}(w), x^q_{i,j,h}, x^n_{i,j,h}$ satisfy equations 2-4 and the above threshold levels.
- Firms value function satisfies equation 5 and $V_{i,h}= -c_{i,h} + \chi_{i,h}\beta\overline{J_{i,h}}$. With free entry, $V_{i,h} = 0$ and $\overline{J_{i,h}} = c_{i,h}/\chi_{i,h}\beta$, where χ is the probability of filling a vacancy in equilibrium
- Wages satisfy $J_{i,f,h}(w^*_{i,f,h}) = J_{i,m,h}(w^*_{i,m,h})$
- Free entry holds, job-finding rate is $M_{i,h}(u_{i,h}, v_{i,h})/u_{i,h} = p_{i,h}(\theta_{i,h})$ and vacancy-filling rate is $M_{i,h}(u_{i,h}, v_{i,h})/v_{i,h} = \chi_{i,h}(\theta_{i,h})$.
- Laws of motion are satisfied: $N_{i,j,h,t+1} = 1 - E_{i,j,h,t+1} - U_{i,j,h,t+1}$

A.3 Flows

cutoff rules and worker flows here.

A.4 Calibration: Misclassification Probabilities

		E	U	N
	E	0.099	0.0019	0.0065
Men	U	0.023	0.089	0.078
	N	0.0066	0.0041	0.098
		E	U	N
	E	0.098	0.0020	0.0154
Women	U	0.0147	0.087	0.1146
	N	0.0042	0.0024	0.099

Table 8: Misclassification Probabilities