The Gender Unemployment Gap: Trend and Cycle

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Abstract

The unemployment gender gap, defined as the difference between female and male rates, was positive until 1980. This gap virtually disappeared after 1980, except during recessions when men's unemployment always exceeds women's. We study the evolution of these gender differences in unemployment from a long run perspective and over the business cycle. Our hypothesis is that the disappearance of the unemployment gender gap was due to the convergence in labor market attachment of men and women. To assess this hypothesis, we examine a three-state search model of the labor market, where agents vary by skill and gender. We find that the model calibrated to match the evolution of the participation patterns by gender, can mostly account for the closing of the gender unemployment gap. In addition, we show that the cyclical properties of the gender gap in unemployment have been stable over the last 60 years, with male unemployment rising more than female unemployment during recessions. We find that gender differences in industry composition are important in recessions, but they do not explain gender differences in employment growth during recoveries. In addition, the behavior of women's unemployment during recoveries is strictly tied to participation, while this relation is more tenuous for men. We also examine evidence from 19 OECD countries and find that convergence in attachment is associated to a decline in the gender unemployment gap in most of those countries. These findings suggest that the historical pattern found for the US holds broadly.

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1 Introduction

This paper studies the gender differences in unemployment from a long run perspective and over the business cycle. Figure 1 shows the evolution of unemployment rates by gender for 1948-2010. The following interesting patterns emerge. The unemployment gender gap, defined as the difference between female and male rates, is positive until 1980, though the gap tends to close during periods of high unemployment. After 1980, the unemployment gender gap virtually disappears, except during recessions when men's unemployment exceeds women's. This phenomenon is particularly pronounced for the last recession.

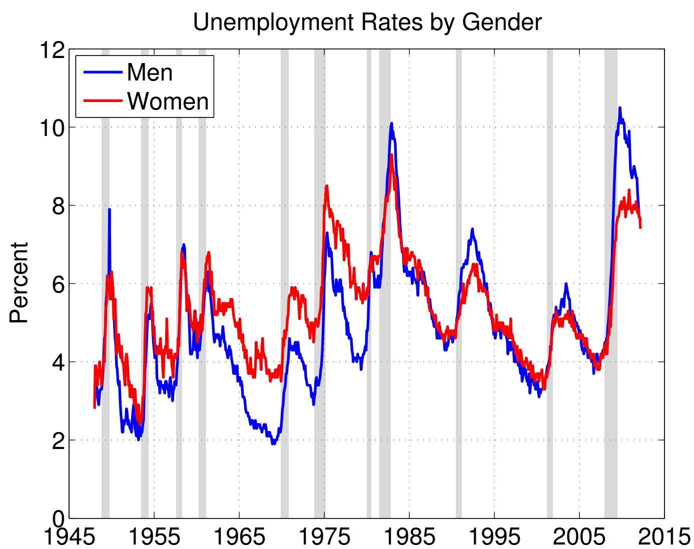

Figure 1: Unemployment by Gender. Source: Bureau of Labor Statistics.

Further examination of the data confirms the visual impression. The gender gap in trend unemployment rates, which starts positive and is particularly pronounced in the 1960s and 1970s, vanishes by 1980. Instead, the cyclical properties of the gender gap in unemployment have been steady over the last 60 years, with male unemployment rising more than female unemployment during recessions. This suggests that the evolution of the unemployment gender gap is driven by structural forces.

We first examine whether the sizable changes in the composition of the labor force can explain the evolution of the unemployment gender gap. The growth in women's education relative to men, changes in the age structure and in the industry distribution by gender can only partially account for its evolution, suggesting that compositional changes are not the major factors driving this phenomenon. Our hypothesis is that the disappearance of the unemployment gender gap is due to the convergence in labor force attachment of men and women, in particular it is a consequence of the decline in male attachment and an increase in female attachment. As is well known, women were less attached to the labor force in the 70s. This low attachment manifested itself in two different dimensions. The first was that among working age married women, a higher fraction was not in

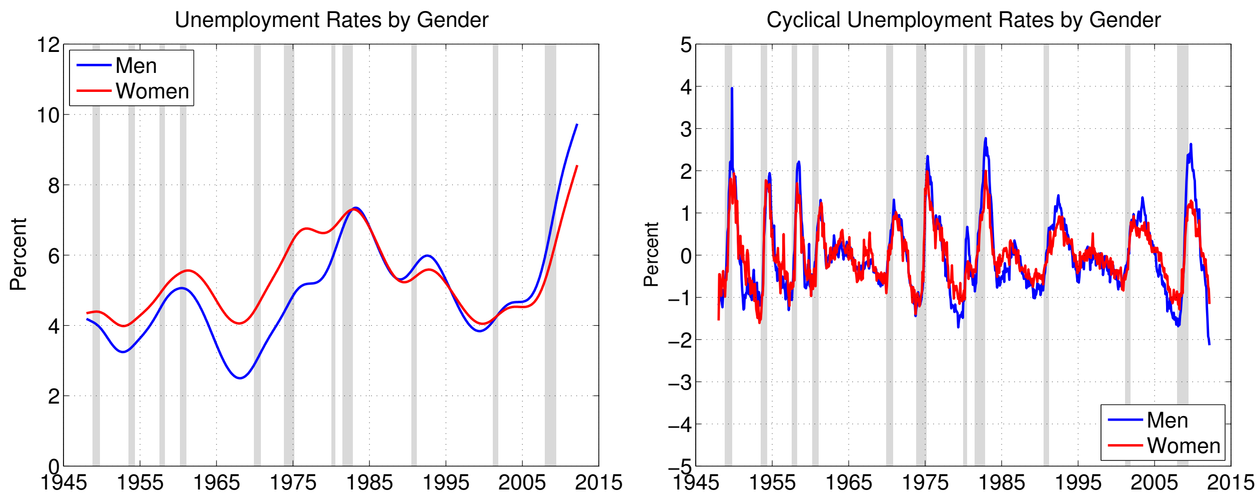

FIGURE 2: Unemployment by Gender: Trend and Cyclical Components. Source: Bureau of Labor Statistics.

the labor force (Goldin, 1990). The female labor force participation rate rose from 43% in 1970 to 60% in 2000. The second is that those who ever participated in the labor force experienced more frequent spells of nonparticipation as documented by Royalty (1998). Even though quantitatively not as stark as women, the pattern was the opposite for men. The male labor force participation rate declined from 80% in 1970 to 75% in 2000. Moreover full-year nonemployment, an indication of permanent withdrawal from the labor force, increased among prime-age men. The amount of joblessness accounted for by those who did not work at all over the year more than tripled, from 1.8% in the 1960s to 6.1% in 1999-2000, (Juhn, Murphy, and Topel, 2002).

The effect of convergence in labor force attachment of men and women is also visible in labor market flows that involve the participation decision. According to Abraham and Shimer (2002), women have become less likely to leave employment for nonparticipation—a sign of increased labor force attachment—while men have become more likely to leave the labor force from unemployment and less likely to re-enter the labor force once they leave it—a sign of decreased labor force attachment. For example, employment-to-nonparticipation flow rates were more than twice as high for women as for men in 1970s and this gap closed by 50% percent by mid-90s. Similarly, there was convergence in flow rates between nonparticipation and unemployment.

To explore this hypothesis, we develop a search model of unemployment populated by agents of different genders. To understand the role of the rise in female labor force attachment, the model differentiates between nonparticipation and unemployment and thus has three distinct labor market states: employment (E), unemployment (U), and nonparticipation (N). Agents of different gender differ by their opportunity cost of being in the labor force and by skill. In every period, employed agents can quit their current position to unemployment or nonparticipation. If they don't quit, they face an exogenous separation shock. If they separate, they may choose unemployment or nonparticipation. Unemployed workers can search for a job or choose not to participate. Workers who are out of the labor force can choose to search for a job or remain in their current state.

Agents' quit and search decisions are influenced by aggregate labor market conditions and their individual opportunity cost of working. This variable, which can be interpreted simply as the value of leisure or the value of home production for an individual worker, is higher on average for women. Individual skills are observable and there are separate job markets for each skill group. Hours of work are fixed and wages are determined by Nash bargaining for men within each skill group. We impose that firms are indifferent between hiring workers of a given skill level. Since workers with greater opportunity cost of working have higher quit rates, and consequently generate lower surplus for the firm, they receive lower wages.

When a firm and a worker meet and agree on a contract, job creation takes place. Before a match can be formed, a firm must post a vacancy. All firms are small and each has one job that is vacant when it enters the job market. The number of jobs is endogenous and determined by profit maximization. Free entry ensures that expected profits from each vacancy are zero. The job finding prospects of each worker are determined by a matching function, following Pissarides (2000). Gender differences in the skill composition and in the distribution of the opportunity cost of being in the labor force determine the gender gaps in participation and unemployment in equilibrium.

We assess the contribution of changing labor market attachment of men and women to the evolution of the gender unemployment gap with a calibrated version of this model. We match the average skill distribution, the participation rate and the unemployment rate by gender in 1978. We then recompute the model for 1996 by allowing for variation in the gender differences in the opportunity cost of being in the labor force to match participation rates by gender in that year, as well as parameters that reflect the variation in outcomes that are exogenous to our model. In particular, we capture the convergence in the gender-specific skill distribution, the rise in the skill premium, and the rise in men's job-loss rate relative to women. We compare the gender unemployment gap implied by the model to the one observed in the data and quantitatively evaluate the contribution of the change in relative attachment of men and women to the decline the gender unemployment gap. We find that our model calibrated to 1996 explains almost all of the convergence in the unemployment rates. The convergence in labor force attachment and the variation in the job-loss rate account for almost all of this convergence. Other exogenous factors have only a minor effect on the closing of the gender unemployment gap.

We also analyze the determinants of unemployment by gender at the cyclical frequency. We find that the unemployment rate rises more for men than women during recessions, and goes down faster for men in the subsequent recoveries. During recoveries, the decline in unemployment is also more pronounced for men, relative to women, but to a smaller degree. We show that this difference can be mostly be explained by gender differences in industry distribution for the 2001 and the 2007-2009 recession, though this factor is less important for the earlier recessions. The sizable within industry differences in employment growth in earlier recessions are driven by the trend differences in participation by gender. We find that industry composition does not play a role in the gender differences in employment growth in the recoveries. We also find that the behavior of women's unemployment during recoveries is strictly tied to participation, while this relation is more tenuous for men. Thus, the gender differences in the trends in participation can account for the differential employment growth by gender in the early recessions and during recoveries.

We conclude with an overview of the international evidence. Based on data from 19 advanced OECD economies starting in 1970, we find that countries with relatively low gender participation gap in the 1970s display a monotonic decline of the gender unemployment gap over the sample period, with the unemployment gap settling on values close to zero as the participation gap stabilizes. In countries with relatively high initial participation gap, the unemployment gap tends to first rise, sometimes sharply, and then fall. This pattern is very similar to the one experienced by the US over the entire post-war period. Differences in labor market structure and culture likely play a large role in determining the size of the gender participation gap and the level of unemployment rate. The experience of the US suggests that the initial rise in the gender unemployment gap is a consequence of an acceleration in the growth of female labor force participation, leading to a dilution of skills and experience associated to with the new female entrants. An additional contributing factor is the rise in the participation of married women, who tend to have low labor market attachment relative to the unmarried women who have historically been prevalent in the female labor force.

The main purpose of our analysis is to provide a framework to understand the determinants of the gender gap in unemployment. Such a framework is clearly essential to explore a number of important questions on policies relating to unemployment. One obvious example is unemployment insurance. Most analyses do not take into account gender differences in the opportunity cost of working and how those may affect the design of an optimal benefit system. Taxation also influences unemployment and participation outcomes. Allowing for gender differences in the responses to tax reforms enables a better assessment of their impact both at the individual and at the household level. Another important dimension of policy is stabilization. Gender gaps in unemployment have received a lot of attention in the most recent business cycle, since men's unemployment rate grew substantially more than women's during the last recession. Our analysis suggests that this outcome is just the result of the ongoing convergence in labor market performance by gender, as the amplitude of the cyclical fluctuations in unemployment has always been greater for men than women in the post-war period. Finally, Manning, Azmat and Guell (2006) have shown that cross-country variation in unemployment rates is mostly driven by differences in women's unemployment. Our findings suggest that these differences may in large part be due to varying paths of female participation and may converge over time.

Our paper contributes to two main strands of literature. A growing literature has analyzed the convergence of labor market outcomes for men and women. See Galor and Weil (1996), Costa (2000), Greenwood, Sheshadri and Yorukoglu (2005), Goldin (2006), Albanesi and Olivetti (2009 and 2010), Fernandez and Wong (2011), and Fernandez (forthcoming). These papers typically focus on the evolution of the labor force participation rate and gender differences in wages. While our model has implications for both participation and wages, our main focus is the evolution of the unemployment gender gap. Our paper is also related to the empirical and theoretical literature on labor market flows. The literature on labor market flows typically focuses on two-state models where there is no role for the participation decision. We build on a recent body of work that incorporates the participation decision into search and matching models such as Garibaldi and Wasmer (2006) and Krusell, Mukoyama, Rogerson, and Şahin (2011, 2012). Our paper is the first paper that studies gender differences in a unified framework.

The structure of the paper is as follows. Section 2 presents the empirical evidence on the changing composition of the labor force and its role in the evolution of the gender unemployment gap. Section 3 introduces our hypothesis. The model is presented in Section 4. The calibration and the quantitative analysis are reported in Section 5. Section 6 discusses the cyclical properties of gender unemployment gaps. Section 7 concludes.

2 Empirical Evidence

The characteristics of the male and female labor forces changed in the last 40 years, potentially affecting the evolution of the unemployment gender gap. There are well-documented patterns for unemployment by worker characteristics. For example, as discussed in Mincer (1991) and Shimer (1998), low-skilled and younger workers tend to have higher unemployment rates. If female workers were relatively younger and less educated before 1980, that could account for their higher unemployment rates. To address this issue, we examine the influence of age and education compositions of the female and male labor force. In addition to these worker characteristics, we consider change in the distribution of men and women across industries.

2.1 Age Composition

We first address the effect of age composition. Figure 3 shows the average age of male and female workers in the labor force. As the figure shows, female workers were relatively young before 1990. This suggests that age composition can potentially contribute to the evolution of the gender gap in unemployment. To assess the quantitative importance of age composition, we first divide the unemployed population into two gender groups, men, m, and women, f. Each group is then divided into three age groups: $A_m = \{$ 16-24, 25-54, 55+ $\}$ and $A_f = \{$ 16-24, 25-54, 55+ $\}$. Let $l_t^s(i)$ be the fraction of workers who are in group i at time t, and let $u_t^s(i)$ be the unemployment rate for workers who are in group i at time t. Then, by definition, the gender-specific unemployment rates at time t is

$$u_t^s = \sum_{i \in A_s} l_t^s(i) u_t^s(i). \tag{1}$$

where $s \in \{m, f\}$. We then calculate a counterfactual unemployment rate, $\tilde{u}_t^f$ for women by assuming that the age composition of the female labor force were the same as men's, i.e. $l_t^f(i) = l_t^m(i)$.

$$\tilde{u}_t^f = \sum_{i \in A_f} l_t^m(i) u_t^f(i). \tag{2}$$

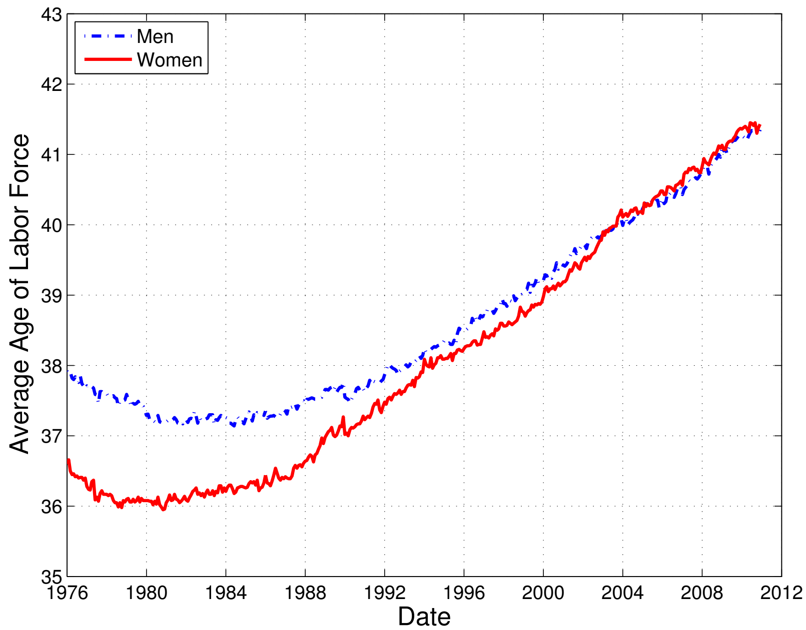

FIGURE 3: Average Age of the Labor Force by Gender. Source: Current Population Survey.

Figure 4 shows both the actual and counterfactual female unemployment rates against the male unemployment rate. Since the female labor force before 1990 was younger than the male labor force, the counterfactual female unemployment rate lies below the actual female unemployment rate. However, this effect is clearly not big enough to explain the gender gap in unemployment rates. After 1990, since the age difference disappears, there is no difference between the actual and counterfactual unemployment rates.

2.2 Education Composition

Another compositional issue is the difference between the skill levels of men and women. Figure 5 shows the male-female ratio of average years of schooling for workers 25 years of age and older.[1] To compute this ratio, we divide the labor force into four education groups, A_e={less than a high school diploma, high school diploma, some college or an associate degree, college degree and above}. We then calculate the average skill of the labor force by gender as

$$\sum_{i \in A_e} l_t^j(i) y(i) \tag{3}$$

where $l_t^j(i)$ is the fraction of education category for gender j and $y(i)$ is the average years of schooling corresponding to that category.[2]

[1] We impose this age restriction since we are interested in completed educational attainment. Consequently, the unemployment rates in Figure 5 are different from the overall unemployment rates.

[2] We use 10 years for less than a high school diploma, 12 years for high school diploma, 14 years for some college or an associate degree, and 18 years for college degree and higher. Note that the education definition changed in the

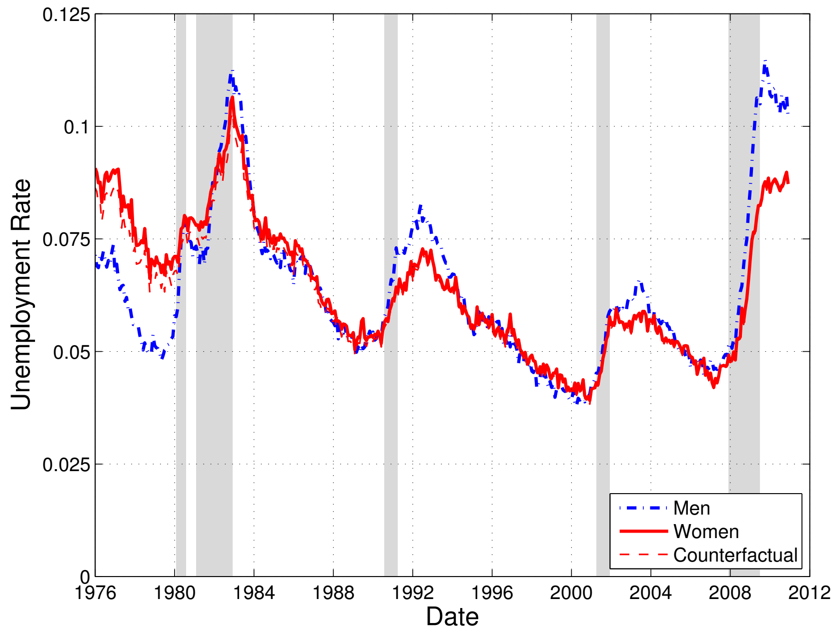

FIGURE 4: Actual and Counterfactual Unemployment Rates (Age). Source: Bureau of Labor Statistics.

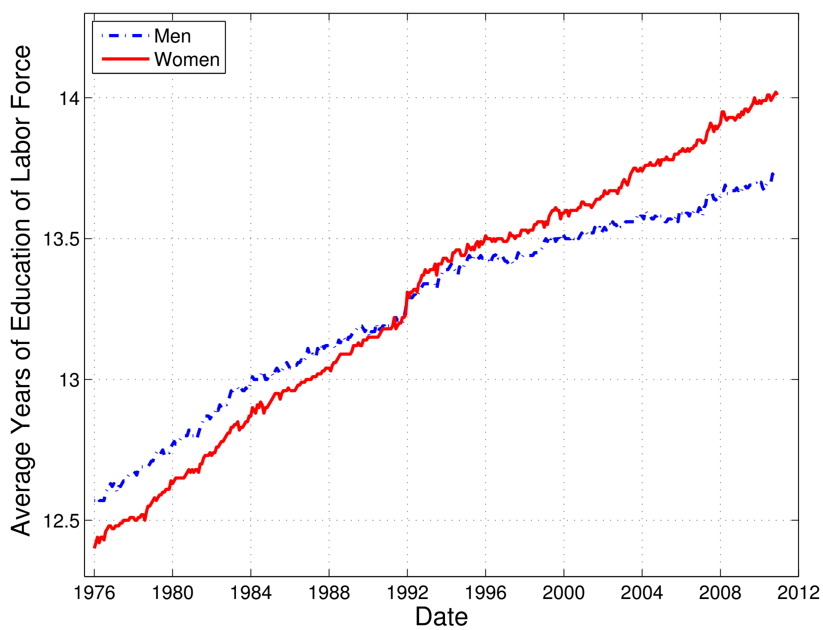

FIGURE 5: Sex Ratio of Education. Source: Bureau of Labor Statistics.

Figure 5 shows that before 1990, female workers were on average less educated than male workers. Between 1990 and 1995, education ratio converged and after 1995, women became more edu-

CPS in 1992. Prior to 1992, categories were High school: Less than 4 years and 4 years and College: 1 to 3 years and 4 years or more. These categories are very similar to the post-1992 ones.

cated. We calculate a counterfactual unemployment rate for women by assigning the male education composition to the female labor force, i.e. $l_t^f(i) = l_t^m(i)$. Figure 6 shows both the actual and counterfactual female unemployment rates against the male unemployment rate. The importance of skill composition is very small until 1990. As female education attainment rises after 1990, the counterfactual unemployment rate for women becomes higher. This counterfactual exercise shows that the change in the skill distribution has had a minimal impact on the gender unemployment gap.

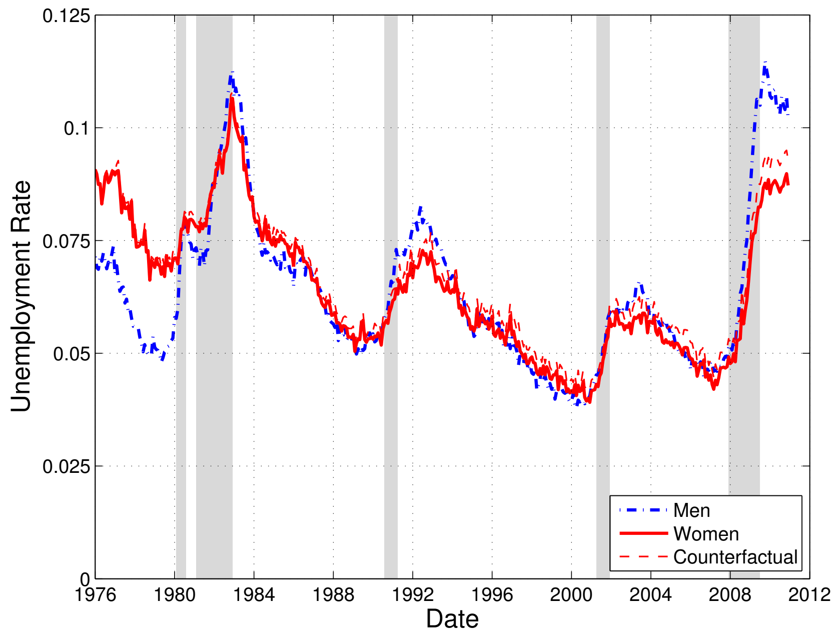

FIGURE 6: Actual and Counterfactual Unemployment Rates (Education). Source: Bureau of Labor Statistics.

2.3 Industry Composition

There have always been considerable differences between the distribution of female and male workers across different industries. Figure 7 shows the fraction of male and female workers employed in the goods-producing, service-providing, and government sectors. In general, goods-producing industries, like construction and manufacturing, employ mostly male workers while most female workers work in the service-providing and government sectors.

We calculate a counterfactual unemployment rate for women by assigning the male industry composition to the female labor force to isolate the role of industry distributions. Figure 8 shows both the actual and counterfactual female unemployment rates against the male unemployment rate. The industry composition does not affect the evolution of trend unemployment rates. However, its impact is important during recessions. If women had men's industry distribution, their unemployment rate would have gone up more during the recessions. If we focus on the three most recent downturns, which occurred after male and female unemployment rates converged, industry

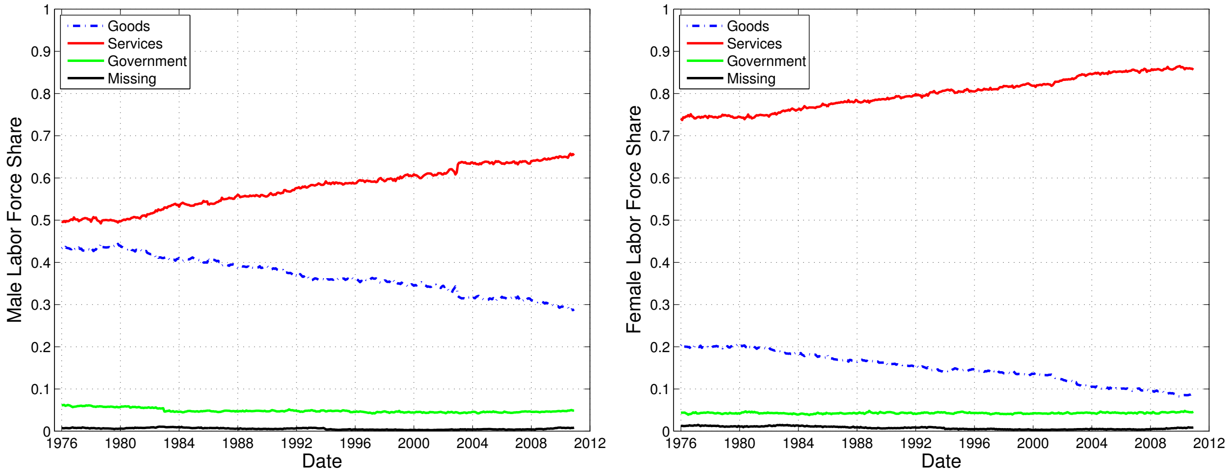

FIGURE 7: The unemployment share of men (left panel) and women (right panel). Source: Bureau of Labor Statistics.

composition explains more than half of the gender gap during the recessions. As for the 1981-82 recession, the counterfactual predicts that the female unemployment rate would have been higher if women's employment patterns were similar to men's.

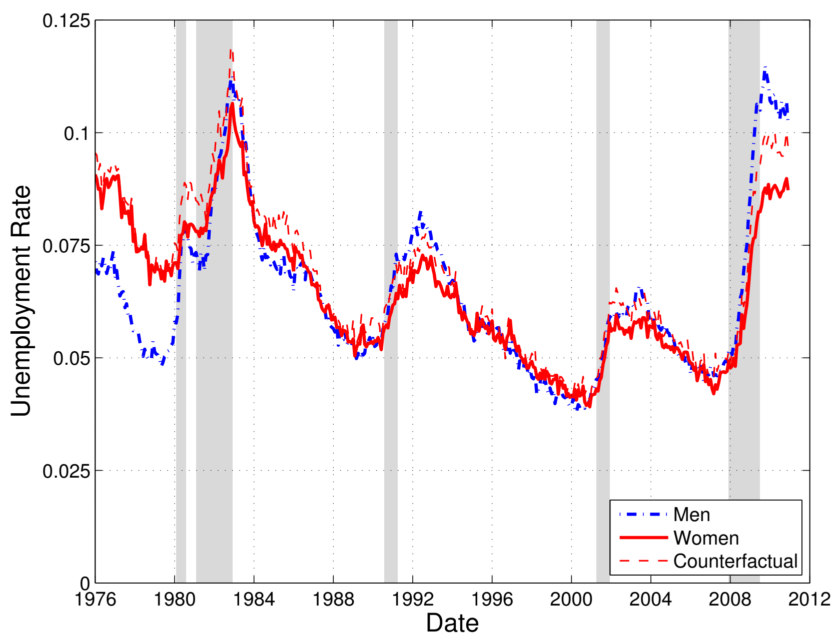

FIGURE 8: Actual and Counterfactual Unemployment Rates (Industry). Source: Bureau of Labor Statistics.

2.4 Occupation Composition

The gender differences in the distribution of workers across occupation has also been sizable, though as can be see in figure 9, these differences have been closing. In general, the share of male workers is higher in production occupations, while the share of female workers is higher in sales and office occupations. To assess the role of occupation composition, we compute a counterfactual unemployment rate for women, in which we assign women the male occupations distribution. The results are displayed in figure 10.

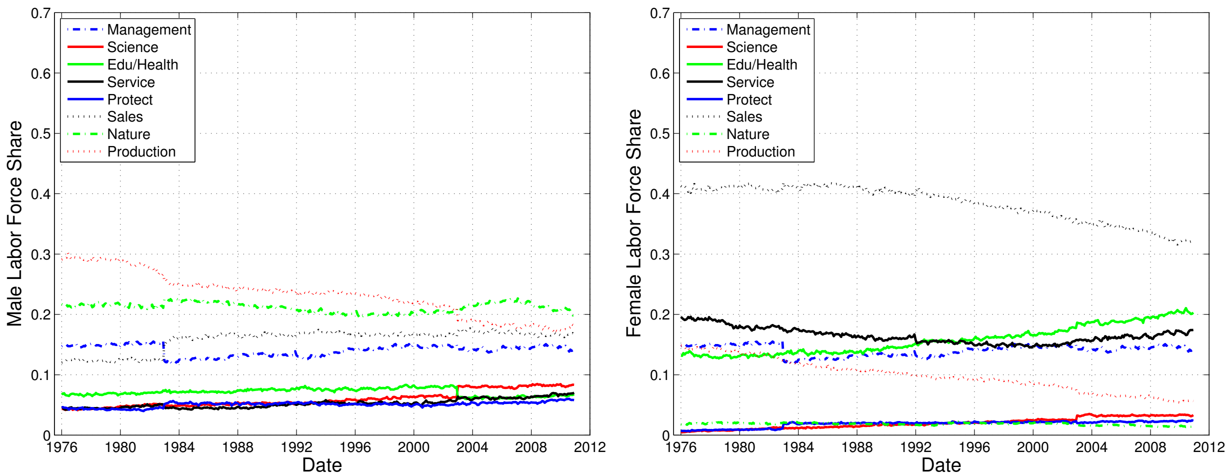

FIGURE 9: The unemployment share of men (left panel) and women (right panel). Source: Bureau of Labor Statistics.

The counterfactual unemployment rate for women is higher that the actually unemployment rate, and higher than men's unemployment rate starting in the mid 1990s. This finding is driven in part by high unemployment rate of women in male dominated occupations in this period, particularly production occupations. This fact may be due to negative selection of women into those occupations.

We also compute a counterfactual unemployment rate for women using the categorization in Acemoglu and Autor (2010), in which occupations are divided into four categories, Cognitive/Non-Routine, Cognitive/Routine, Manual/Non-Routine, and Manual/Routine. As shown in figure 11, the share of men in Manual/Routine tasks is relatively high, while the share of women in high in Manual/Non-Routine tasks. Moreover, the share of women in Cognitive/Non-Routine tasks, which started out lower than men's, has been ground at a faster rate than men's, leading to a 60% share of Non-Routine tasks for women by 2010, compared to a share of 45% for men. Acemoglu and Autor (2010) document the decline of employment in routine tasks starting in the 1990s, which could have led to a corresponding rise in the unemployment rate for men, relative to women. Figure 12 suggests that female unemployment would have indeed been higher since the early 1990s if their occupation composition was the same as men's. However, occupation composition with this categorization does not account for the gender unemployment gap in the early years of the sample.

We conclude that gender differences in age, skill, and industry composition can not account for

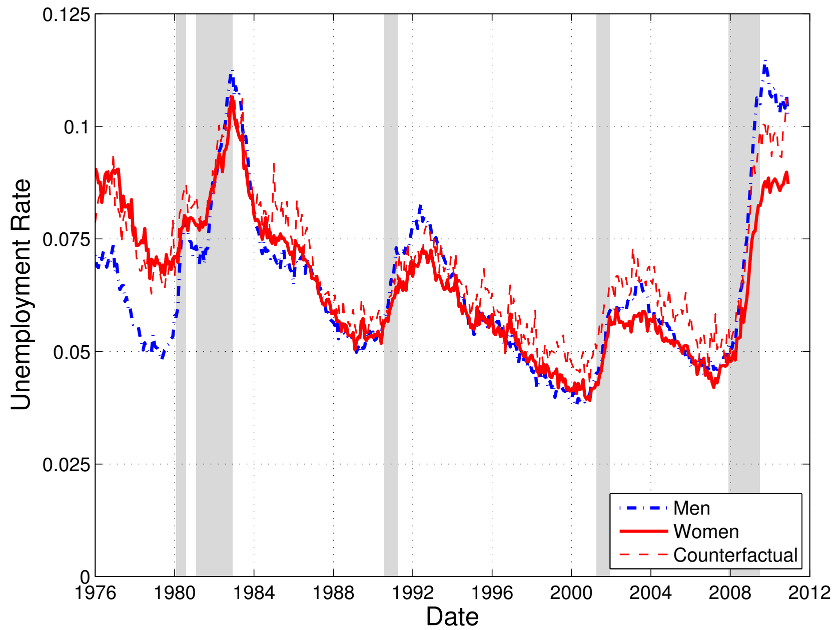

FIGURE 10: Actual and Counterfactual Unemployment Rates (Occupation). Source: Bureau of Labor Statistics.

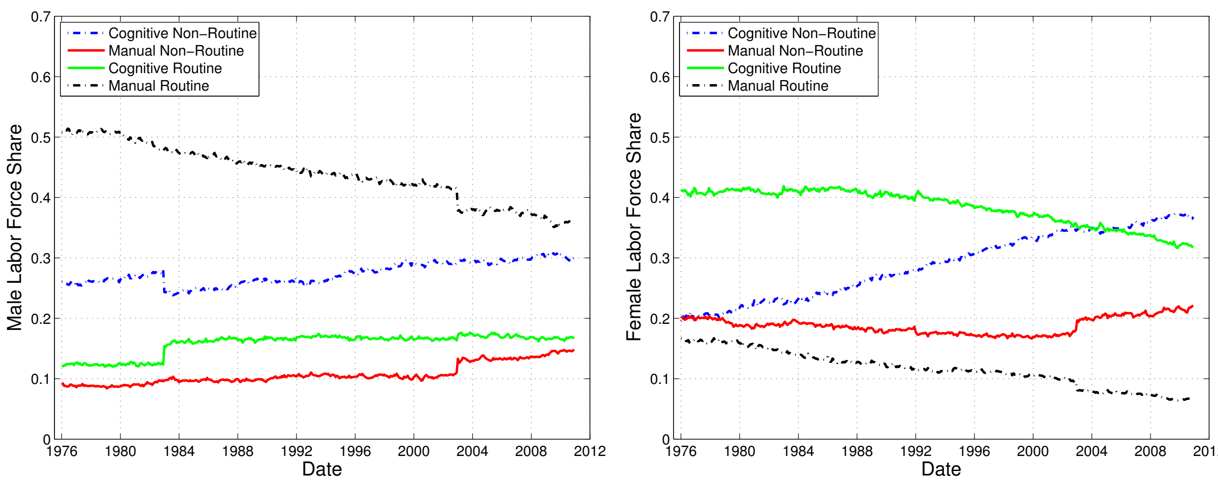

FIGURE 11: The unemployment share of men (left panel) and women (right panel). Occupations grouped following Acemoglu and Autor (2010). Source: Bureau of Labor Statistics.

the evolution of the gender unemployment gap. However, we find that industry distribution plays an important role in explaining cyclical patterns.

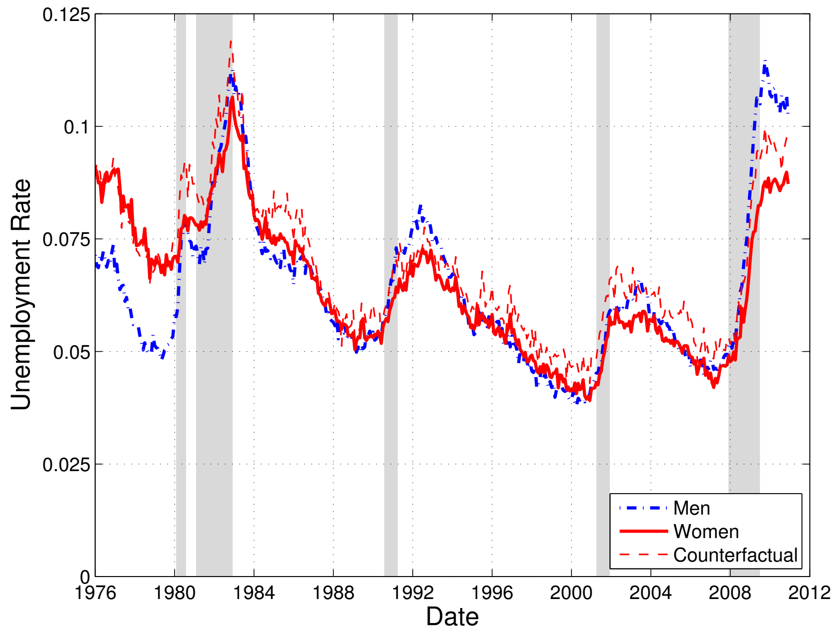

FIGURE 12: Actual and Counterfactual Unemployment Rates (Occupation). Occupations grouped following Acemoglu and Autor (2010). Source: Bureau of Labor Statistics.

3 Our Hypothesis: Convergence in Labor Force Attachment

Our hypothesis is that the evolution of the gender unemployment gap was due to the convergence in labor market attachment of women and men. As women have become more attached to the labor force, men have become less attached, reducing the difference in the degree of labor force attachment. Figure 13 shows the evolution of the labor force participation rate for men and women starting in 1970.

Women were less attached to the labor force in the 70s. This low attachment manifested itself in two different dimensions. First, among working age women a higher fraction was not in the labor force (Goldin, 1990). Second, those who ever participated in the labor force experienced more frequent spells of nonparticipation, as documented by Royalty (1998). The second component of increased labor force attachment of married women is that they experience less frequent spells of nonparticipation, especially in childbearing years. The evolution of labor force behavior in connection to pregnancy and child birth is documented in the 2008 Current Population Report on "Maternity Leave and Employment Patterns of First-time Mothers: 1961-2003." This report shows that women are now more likely to work both during pregnancy and after child birth. As shown in the bar chart in figure 14, whereas in 1976-1980, the fraction of women who stopped working two months or more before the end of pregnancy was 41%, that ratio dropped to 23% in 1996-2000. Among women who worked during pregnancy 36% quit their jobs in 1981-1985 and this fraction dropped to 26% by 1996-2000. Leave arrangements that allow women to keep their positions became more widespread. The fraction of women who used paid/unpaid leave after childbirth increased from

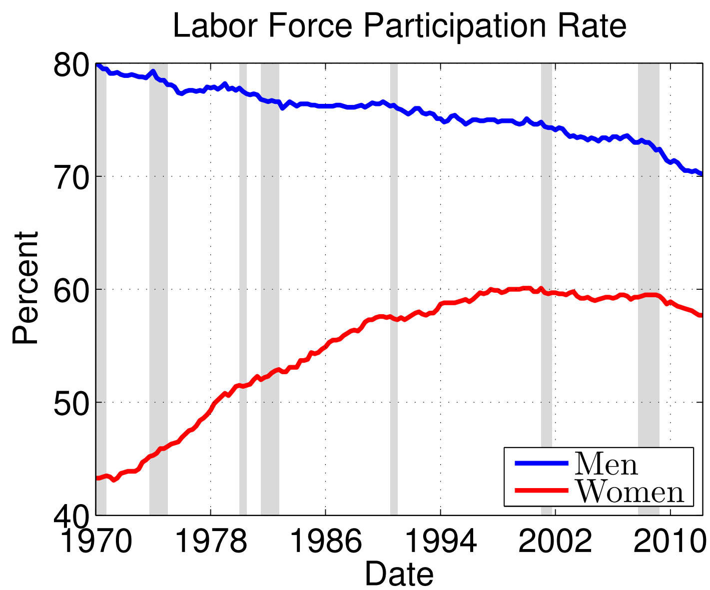

FIGURE 13: Labor force participation rate by gender. Source: Current Population Survey.

71% in 1981-1985 to 87% in 1996-2000.[3]

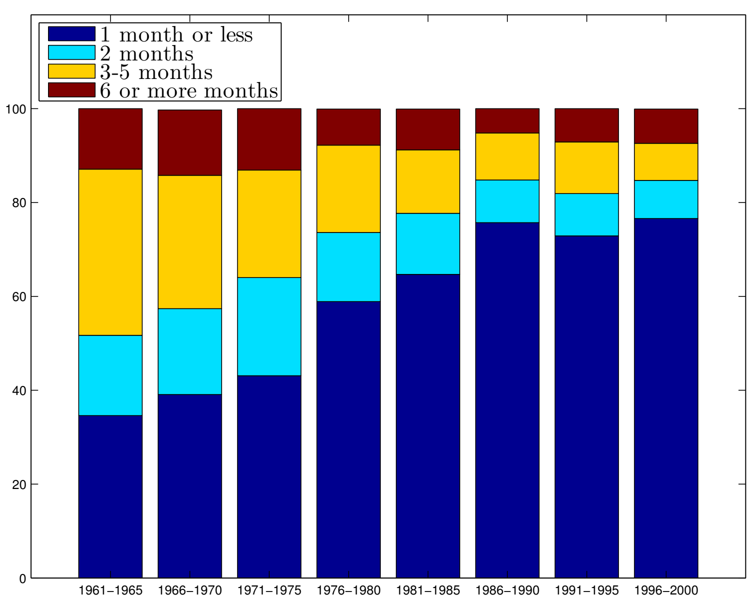

FIGURE 14: Source: 2008 Current Population Report on "Maternity Leave and Employment Patterns of First-time Mothers: 1961-2003."

For men, the pattern for labor force attachment was the opposite. The labor force participation rate of men declined from 80% in 1970 to 75% in 2000. Moreover full-year nonemployment, an indication of permanent withdrawal from the labor force, increased among prime-age men. The

[3]See Table 5 in the report.

amount of joblessness accounted for by those who did not work at all over the year more than tripled, from 1.8% in the 1960s to 6.1% in 1999-2000, (Juhn, Murphy, and Topel, 2002). The decline in male participation is typically attributable to two factors: an expansion of the disability benefits program (Autor and Duggan, 2003) and low levels of real wages of less-skilled men during the 1990s (Juhn, Murphy, and Topel, 2002).

Another dimension that convergence in attachment manifests itself is the convergence in the duration of unemployment by gender as discussed in Abraham and Shimer (2002). Figure 15 plots the evolution of average duration of men and women. As the figure shows, men on average experienced substantially longer unemployment spells relative to women until 90s. Starting in 90s, women's average duration of unemployment converged to similar values as men's.

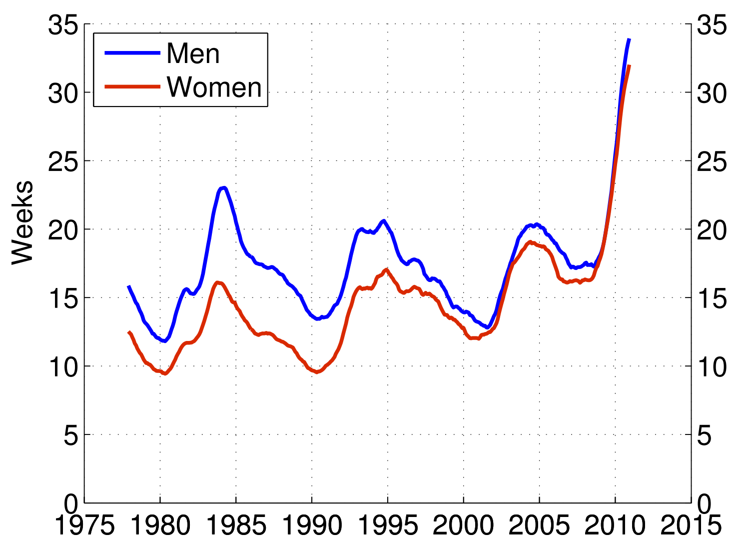

FIGURE 15: Duration of unemployment for men and women. Source: Current Population Survey.

Relatedly, the convergence in labor force attachment of men and women has also affected the labor market flow rates that involve the participation decision. According to Abraham and Shimer (2002), women have become less likely to leave employment for nonparticipation—a sign of increased labor force attachment—while men have become more likely to leave the labor force from unemployment and less likely to re-enter the labor force once they leave it—a sign of decreased labor force attachment. For example, employment-to-nonparticipation flow rates were more than twice as high for women as for men in 1970s and this gap closed by 50% percent by mid-90s as shown in Figure 16. Similarly, there was convergence in flows rates between nonparticipation and unemployment. In Section 5, we report the gender-specific flow rates for 1978 and 1996.

The empirical evidence suggests strong convergence in labor force attachment for men and women. However, at first glance, it is not obvious that all these patterns are consistent with a closing unemployment gender gap. Most importantly, we have discussed that women's duration of unemployment increased relative to men's starting in 90s. An increase in the duration of un-

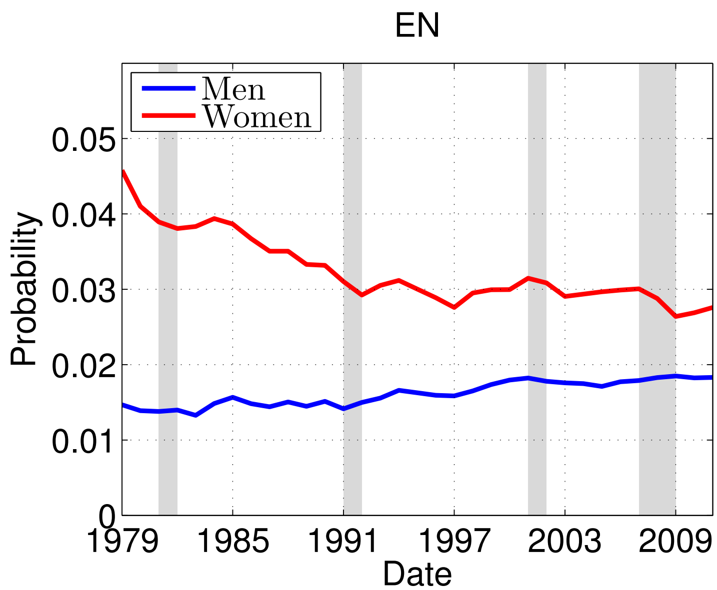

FIGURE 16: Employment to nonparticipation flow rates by gender. Source: Current Population Survey.

employment clearly causes an increase in the unemployment rate and seem inconsistent with our hypothesis. It is true that if attachment only affected the duration of unemployment for women, everything else being equal, female unemployment rate would have risen. However, this is not the only dimension that a rise in attachment affects labor market outcomes. As female attachment rose, women became less likely to leave employment for nonparticipation and return to the labor force after nonparticipation spells. These changes both caused a drastic increase in employment, counteracting the rise in the unemployment duration.

To summarize, the evidence we surveyed suggests that the evolution of the gender gap in unemployment cannot be accounted for in isolation from the drastic change in women's labor force participation and the relatively smaller but still evident decline in men's participation. Therefore, in the next section, we examine a search model of unemployment with a participation margin in order to capture the joint evolution of participation and unemployment gender gaps.

4 Model

We consider an economy populated by agents of different genders, in equal numbers. Agents are risk neutral. They differ by their opportunity cost of being in the labor force and by skill.[4] There are three distinct labor market states: employment, unemployment and nonparticipation. In every period, employed agents can quit their current position into unemployment or nonparticipation.

[4]The skill distribution by gender is exogenous as the model abstracts from human capital investment decisions. We also exclude differences in marital status, even as most of the convergence in labor force participation rates and unemployment rates by gender in the aggregate are determined by the behavior of married women. This modeling choice is driven by the fact that some key labor market statistics we use in the calibration are not available by marital status, or are subject to large measurement error at that level of disaggregation.

If they don't quit, they face an exogenous separation shock. If they separate, they may choose unemployment or nonparticipation. Unemployed workers can search for a job or choose not to participate. Workers who are out of the labor force can choose to search for a job or remain in their current state.

Agents' quit and search decisions are influenced by their individual opportunity cost of working. This variable, which varies by gender, can be interpreted simply as the value of leisure or the value of home production for an individual worker. Thus, the distribution of agents across different labor market states is endogenously determined. We assume that the individual opportunity cost of working is private information, and the distribution of this cost is publicly observed.

Individual skills are observable and there are two skill levels with separate job markets. Hours of work are fixed and wages are determined according to a surplus splitting arrangement for men within each skill group. We consider a variety of wage determination mechanisms for women. Our benchmark case is one in which firms are made indifferent between hiring workers of a given skill level. Since workers with greater opportunity cost of working (women) have higher quit rates, and consequently generate lower surplus for the firm, they will receive lower wages. This mechanism endogenously generates gender wage gaps, within each skill group.

When a firm and a worker meet and form a match, job creation takes place. Before a match can be formed, a firm must post a vacancy. All firms are small and each has one job that is vacant when they enter the job market. The number of jobs is endogenous and determined by profit maximization. Free entry ensures that expected profits from each vacancy are zero. The job finding prospects of each worker are determined by a matching function, following Pissarides (2000).

4.1 Workers' Problem

The economy is populated by a continuum of unit measure of workers, of different gender, $j = f, m$. Workers of each gender also differ by skill, where h denotes high skill workers, and l low skill workers. Worker skill affects productivity, y_i, with $i = h, l$, with $y_h > y_l$.

Each worker can be in one of three states: employed, unemployed, or out of the labor force. In addition, each worker is characterized by her realization of an idiosyncratic shock $x \geq 0$. This variable represents the opportunity cost of being in the work force and can be interpreted as the value of home production for the worker. The cumulative distribution function of x is represented by $F_j(x)$ for $j = f, m$, which is i.i.d. over time and across workers of a given gender. We assume that x follows a Pareto distribution and allow the tail index and threshold parameters to vary by gender.

The flow values for the worker of type ij, depend on her realized value of x and her labor market status, and if she is employed, on the wage, w. They are defined as follows. For the employed:

$$v_{ij}^W(x, w) = w + (1 - e)x,$$

for the unemployed:

$$v_{ij}^{S}(x) = (1-s)x,$$

and for individuals out of the labor force:

$$v_{ij}^{H}(x) = x,$$

where $e \in (0,1]$ is the fraction of time devoted to market work if employed, $s \in [0,1]$ is the fraction of time devoted to job search if unemployed. The values of a worker as a function of their current x will be denoted by $W_{ij}(x,w)$ for employed workers, $S_{ij}(x)$ for unemployed workers and $H_{ij}(x)$ for workers who are out of the labor force.

Each individual draws a value of x at time 0 and samples a new draw of x in each period with probability $\lambda_{ij} \in [0,1]$. With probability $1-\lambda_{ij}$ and individual's x remains the same as in the previous period. We assume that the new value of x, denoted with x', is drawn at the beginning of the period. In addition, employed agents may experience an exogenous separation shock, with probability $\delta_{ij} \in (0,1)$, while unemployed agents may receive a job offer with probability $p_i \in [0,1]$ which is determined in equilibrium.[5] The separation and job finding shocks for that period are also realized before the agent can make any decisions. Under this assumption on timing, an agent who has received a new value of x, x', faces the following decisions during the period:

- If she is unemployed and does not receive a job offer, she chooses $max\{S_{ij}(x'), H_{ij}(x')\}$, with reservation strategy of remaining unemployed for $x' < x_{ij}^{n}$ and exiting the labor force for $x' \geq x_{ij}^{n}$. If she does receive a job offer, her choice is $max\{W_{ij}(x'), S_{ij}(x'), H_{ij}(x')\}$. This problem can be rewritten as: $max\{max\left\{W_{ij}(x'), S_{ij}(x')\right\}, H_{ij}(x')\}$. The reservation strategy for the internal maximization is to remain employed if $x' \leq x_{ij}^{a}$ and to become unemployed otherwise. If the worker chooses unemployment, then the external maximization problem is $max\left\{W_{ij}(x'), H_{ij}(x')\right\}$. The optimal reservation strategy for this problem is to remain employed for $x' < x_{ij}^{q}$ and to exit the labor force for $x' \geq x_{ij}^{q}$.

- If she is out of the labor force, she chooses $max\{H_{ij}(x'), S_{ij}(x')\}$, with cut-off level x_{ij}^{n}, with corresponding reservation strategy of becoming unemployed for $x' < x_{ij}^{n}$ and exiting the labor force for $x' \geq x_{ij}^{n}$.

- If employed and with no separation shock, she solves $max\{W_{ij}(x'), S_{ij}(x'), H_{ij}(x')\}$. This problem can be rewritten as: $max\{max\left\{W_{ij}(x'), S_{ij}(x')\right\}, H_{ij}(x')\}$. The reservation strategy for the internal maximization is to remain employed if $x' \leq x_{ij}^{a}$ and to become unemployed otherwise. If the worker chooses employment, then the external maximization problem is $max\left\{W_{ij}(x'), H_{ij}(x')\right\}$. The optimal reservation strategy for this problem is to remain em-

[5] We allow the probabilities λ and δ to vary by gender and skill in order to match selected labor market flow rates by gender and skill in the quantitative analysis. The job finding rate p will vary by skill in equilibrium, thus, we incorporate this feature in the worker's problem.

ployed for $x' < x_{ij}^q$ and to exit the labor force for $x' \geq x_{ij}^q$. If she chooses to exit to unemployment, than the external problem is $max\left\{S_{ij}(x'), H_{ij}(x')\right\}$, with reservation strategy to remain unemployed for $x' \leq x_{ij}^n$ and to exit the labor force otherwise. If she does receive a separation shock, she solves $max\{H_{ij}(x'), S_{ij}(x')\}$, with corresponding reservation strategy of becoming unemployed for $x' < x_{ij}^n$ and exiting the labor force for $x' \geq x_{ij}^n$.

A worker who does not receive a new value of x at the end of the period faces the following outcomes:

- If she is unemployed, she draws a job offer with probability p_i. If she receives a job offer, her choice is $max\{W_{ij}(x), S_{ij}(x)\}$, with corresponding reservation strategy of accepting the offer for $x < x_{ij}^a$ and rejecting it for $x \geq x_{ij}^a$. If she does not receive a job offer, she continues to remain unemployed.

- If she is out of the labor force, she continues in that state.

- If she is employed, she continues in that state if she does not receive a separation shock. If she is hit by a separation shock, then she chooses $max\{S_{ij}(x'), H_{ij}(x')\}$, with corresponding reservation strategy of becoming unemployed for $x < x_{ij}^n$ and exiting the labor force for $x \geq x_{ij}^n$.

Since x is i.i.d., an unemployed worker with a job offer has the same problem of an employed worker who has not been separated. Similarly, an employed worker who has just been separated faces the same choice as an unemployed worker without a job offer.

The optimal choices of a worker depend on the wage she will face if employed. Thus, the cut-offs $x_{ij}^n(w)$, $x_{ij}^a(w)$, and $x_{ij}^q(w)$, which correspond to the policy functions for the individuals' problem, also depend on the wage. The corresponding value functions are:

$$\begin{aligned} S_{ij}(x;w) &= v_{ij}^S(x) + \lambda_{ij}\beta \int_{\underline{x}_j}^{\overline{x}_j} \left[p_i max\left\{W_{ij}(x';w), S_{ij}(x';w), H_{ij}(x';w)\right\}\right] dF_j(x') \\ &\quad + \lambda_{ij}\beta \int_{\underline{x}_j}^{\overline{x}_j} \left[(1-p_i) max\left\{S_{ij}(x';w), H_{ij}(x';w)\right\}\right] dF_j(x') \\ &\quad + (1-\lambda_{ij})\beta\left[p_i max\left\{W_{ij}(x;w), S_{ij}(x)\right\} + (1-p_i)S_{ij}(x;w)\right], \end{aligned} \tag{4}$$

for unemployed workers,

$$H_{ij}(x;w) = v_{ij}^H(x) + \lambda_{ij}\beta \int_{\underline{x}_j}^{\overline{x}_j} max\left\{S_{ij}(x';w), H_{ij}(x';w)\right\} dF_j(x') + (1-\lambda_{ij})\beta H_{ij}(x;w), \tag{5}$$

for nonparticipants, and

$$
\begin{aligned}
W_{ij}(x;w) &= v_{ij}^{W}(x;w) + \lambda_{ij}\beta \int_{\underline{x}_j}^{\overline{x}_j} \left[(1-\delta_{ij}) max \left\{W_{ij}(x';w), S_{ij}(x';w), H_{ij}(x';w)\right\}\right] dF_j(x') \\
&+\lambda_{ij}\beta \int_{\underline{x}_j}^{\overline{x}_j} \left[\delta_{ij} max \left\{S_{ij}(x';w), H_{ij}(x';w)\right\}\right] dF_j(x') \\
&+(1-\lambda_{ij})\beta \left[(1-\delta_{ij})W_{ij}(x;w) + \delta_{ij} max \left\{S_{ij}(x;w), H_{ij}(x;w)\right\}\right], \qquad (6)
\end{aligned}
$$

for employed workers, with $i = h, l$ and $j = f, m$, where $\beta \in (0,1)$ is the discount factor. The solution to these optimization problems give rise to worker flows in equilibrium. The pattern of worker flows depends on the relation between the cut-off levels $x_{ij}^{q}(w)$, $x_{ij}^{n}(w)$ and $x_{ij}^{a}(w)$ that define the reservation strategies. We derive these in Appendix A.

4.2 Firms' Problem and Equilibrium

There are separate job markets for each skill group and wages are chosen to split the surplus between the firm and the worker, given that firms do not observe the worker's individual opportunity cost of working. This implies that wages may only depend on gender within each skill group. In addition, since the distribution of x depends on gender, the value of a job filled by a female and a male worker is different. In particular, since x is on average higher for women, women have higher quit rates and generate lower surplus for the firm. If the difference in surplus generated by a male and female worker is larger than the discounted vacancy creation cost, then the firms will not hire women. To rule out this outcome, we first determine the wage for men for each skill group and then consider different alternatives for female wages. Our baseline case imposes that female wages are such that the surplus to a firm is equalized across genders. This mechanism endogenously generates gender wage gaps, within each skill group. This wage determination mechanism links labor force attachment to gender differences in wages. As we show in the next section, less than 20% of gender differences are explained by this channel. In Section 5.5, we consider various other wage-setting mechanisms and repeat our quantitative experiments using these mechanisms.

Wage and Profit Functions Production is carried out by a continuum of unit measure of firms using only labor. Firms are active when they hire a worker, and each firm can hire at most one worker. Each firm posts a vacancy, at a cost $c > 0$, in order to hire a worker who will produce in the following period. There is free entry in the firm sector.

All workers with the same skill level are equally productive. Since the individual opportunity cost of working is private information, wages vary by skill and by gender, as we describe below.

The value of a filled job at wage w, which we denote as $J_{ij}(w)$, is given by:

$$J_{ij}(w) = y_i - w + \beta \left\{ \int_{\underline{x}_j}^{min\left\{x^q_{ij}(w), x^a_{ij}(w)\right\}} \left[(1-\delta_{ij})J'_{ij}(w) + \delta V_i\right] dF_j(x') + \int_{min\left\{x^q_{ij}(w), x^a_{ij}(w)\right\}}^{\overline{x}_j} V_i dF_j(x') \right\}. \tag{7}$$

The first term is flow value of a filled job, given by productivity minus the wage. Firms discount the future at the same rate as workers. As discussed above, workers may quit to unemployment or nonparticipation if $x > min(x^q_{ij}(w), x^a_{ij}(w))$. If the worker does not quit, the job could still get destroyed exogenously with probability δ . In this case, the firm creates a vacancy with value V_i. If the worker does quit, the firm will again create a vacancy. As long as x is i.i.d., $J_{ij}(w)$ does not depend on x.

We assume that x is not observed, while gender and skill are observed. Firms offer a wage w_{ij} conditional on observables, based on their assessment of the the characteristics of workers who they might be matched to. We assume that firms know the distribution of characteristics of currently unemployed workers. However, this distribution itself depends on the wage being offered by firms. Thus, to compute the equilibrium wage, we procede as follows. Let w_{ij} denote a candidate equilibrium wage based on which workers choose to be in the labor force, given their value functions W, S, H and their policy fuctions $x^a_{ij}(w)$, $x^q_{ij}(w)$, $x^n_{ij}(w)$. Then, firms will choose a wage $\hat{w}_{ij}$ to solve the following surplus splitting problem:

$$w_{im} = argmax_{\hat{w}} \left[\int_{\underline{x}_m}^{min\{x^a_{im}(w_m),\, x^q_{im}(w_{im})\}} max\left\{0, (W_{im}(x;\hat{w}) - max\left\{H_{im}(x;\hat{w}), S_{im}(x;\hat{w})\right\})\right\} dF_m(x) \right]^{\gamma} \times \left[J_{im}(\hat{w}) QJ_{im}(\hat{w}, w_{im}) - V_i\right]^{1-\gamma}, \tag{8}$$

where

$$QJ(\hat{w_{ij}}, w_{ij}) = \frac{\int_{\underline{\mathrm{x}}_j}^{min\{x^a_{ij}(\hat{w}_{ij}),\, x^q_{ij}(\hat{w}_{ij})\}} dF_j(x)}{\int_{\underline{\mathrm{x}}_j}^{min\{x^a_{ij}(w_{ij}),\, x^q_{ij}(w_{ij})\}} dF_j(x)},$$

for $j = f, m$. Here, $W_{im}(x;w) - max\left\{H_{im}(x;w), S_{I'm}(x;w)\right\} \geq 0$ is the surplus for the worker, $J_{im}(\hat{w_{im}}) - V_i \geq 0$ is the surplus for the firm and $0 \leq \gamma \leq 1$ is the bargaining weight of the worker.

The function $QJ(\hat{w_{ij}}, w_{ij})$ represents the fraction of workers of type ij who are in the labor force who would accept a job offer at wage $\hat{w_{ij}}$, given that the candidate equilibrium wage is w_{ij}. With this formulation, the firm understands that by offering a lower wage it will reduce the size of the pool of workers that will accept the job, and conditional on accepting, workers will be more likely to quit. On the other hand, a lower wage will increase current profits for the firm. The solution to this wage setting problem delivers a policy function: $\hat{w}_{ij}(w)$. The fixed point of this policy function constitutes the equilibrium wage:

$$w^*_{ij} = \hat{w_{ij}}(w^*_{ij}).$$

Since the opportunity cost of work, x, is privately observed and wages do not vary with this variable, low x workers will earn informational rents, which will reduce the surplus of the firm.

In the baseline wage determination mechanism, we impose that firms are indifferent between hiring female and male workers, given skill. Thus, we determine female wages conditional on skill levels by imposing:

$$J_{if}(\hat{w}_{if})QJ_{if}(\hat{w}_{if}, w_{if}) = J_{im}(\hat{w}_{im})QJ_{im}(\hat{w}_{im}, w_{im}) \tag{9}$$

for $i = h, l$. This restriction pins down the female/male wage ratio for each skill level. We denote with $\overline{J}_i$ the optimal value of a filled job.

Since the value of a filled job does not depend on gender, the value of a vacancy only depends on skill and is given by:

$$V_i = -c + \chi_i \beta \overline{J}_i, \tag{10}$$

for $i = h, l$, where χ_i is the probability of filling a vacancy, determined in equilibrium.

Equilibrium Conditions We assume free entry so that $V_i = 0$ for $i = h, l$. This implies that in equilibrium, using equation 9, the following restriction will hold:

$$\overline{J}_i = c/\chi_i \beta. \tag{11}$$

for $i = h, l$.

Following Pissarides (2000), firms meet workers according to the matching function, $M_i(u, v)$ for $i = h, l$, where u is the number of unemployed workers and v is the number of vacancies. $M_i(\cdot)$ is increasing in both arguments, concave, and homogeneous of degree 1. The ratio $\theta_i = v_i/u_i$ corresponds to market tightness in the labor market for workers with skill $i = h, l$. Then, the job finding rate is:

$$p_i := M_i(u_i, v_i)/u_i = p_i(\theta_i), \tag{12}$$

while the probability that a vacancy will be filled is:

$$\chi_i := M_i(u_i, v_i)/v_i = \chi_i(\theta_i), \tag{13}$$

with $p_i'(\theta_i) > 0$ and $\chi_i'(\theta_i) < 0$, with $p_i(\theta_i) = \theta_i \chi_i(\theta_i)$ for $i = h, l$.

4.3 Stationary Equilibrium

Since there are no aggregate shocks, we consider stationary equilibria defined as follows:

- Household value functions, $S_{ij}(x)$, $H_{ij}(x)$ and $W_{ij}(x)$ satisfy equations 4, 5, and 6.
- Firms' value functions, J_{ij} and V_i satisfy equations 7 and 10.
- Wages satisfy equations 8 and 9.

- The job-finding and vacancy-filling rates satisfy equations 12 and 13, and the free entry condition (equation 11) holds.
- The laws of motion for U, E, and N, derived in Appendix A are satisfied.

5 Quantitative Analysis

We now proceed to calibrate the model to match 1978 data and run a series of experiments to assess the contribution of rising female labor market attachment to the convergence of unemployment rates by gender.

5.1 Calibration

We choose 1978 as a base point for the calibration. This choice is motivated by the fact that detailed gross flows data become available starting from 1976 and 1978 is the midpoint between the peak and trough of the 75-80 expansion. The gender gap in unemployment in 1978 is equal to the average of this variable in the 70s.[6] Our general strategy is to calibrate the model to 1978 to match some key moments in the data.

We first set some of the parameters using independent evidence. We interpret the model as monthly and set the discount rate, β, accordingly to 0.996. We target the population of workers older than 25 years of age since we focus on completed education. We set the educational composition of the labor force by skill and gender to their empirical values in 1978. We assume that the matching function is Cobb-Douglass and set the elasticity of the matching function with respect to unemployment, α, to 0.72 following Shimer (2005). Worker's bargaining power, γ, is set to the same value.[7] We set e to 0.625 corresponding to a work day of 10 hours out of 16 active hours. The parameter s is calibrated to 0.125 to match the 2 hour per day job search time reported in Krueger and Mueller (2011). We set the vacancy creation cost parameter, c, to 8.7, corresponding to about three months of wage for skilled male workers. We set the lower band on the distribution of the support for x to zero for both genders. Table 1 summarizes the calibration of these parameters.

e	s	β	α	γ	μ	y_s/y_u	c	$\underline{x}_f$	$\underline{x}_m$
0.625	0.15	0.996	0.72	0.72	0.15	1.4565	8.7	0	0

Table 1: Parameter values.

The rest of the parameters are set to match a set of salient statistics in the data. These moments are: the skill premium, the labor force participation rate by gender, the unemployment

[6] As we have shown, male unemployment rate is more cyclical leading to cyclicality in the gender unemployment gap. By picking the midpoint of the expansion, we tried to isolate the long-term behavior of the unemployment gender gap.

[7] This choice does not guarantee efficiency in this model since the Hosios condition need not hold given our wage-setting mechanism.

rate by gender, the EU and EE flow rates by gender and skill. The parameters we use to match these statistics are y_i, κ_j, $\overline{x}_j$, λ_{ij}, and δ_{ij} for $i = f, m$ and $j = u, s$. Here κ_j is the shift parameter of the Pareto distribution for x for gender j while $\overline{x}_j$ is the upper bound for the support of x in the discretized distribution we use in the computation. All these parameters jointly determine the model outcomes we target, though y_j is the most important parameter for matching the skill premium, κ_i and $\overline{x}_i$ are key for matching the labor force participation and the unemployment rates by gender, λ_{ij} and δ_{ij} are most relevant for matching the flows. Table 2 shows the calibrated values and calibration targets and Figure 26 in Appendix B shows the distribution of x for men and women.

		Population share	δ	λ	$\bar{x}$	κ
Women	Unskilled	0.465	0.0042	0.0096	9.73	50
	Skilled	0.067	0.0048	0.0123		
Men	Unskilled	0.375	0.0084	0.0120	7.13	5
	Skilled	0.093	0.0042	0.0100		

Table 2: Gender and skill specific parameter values.

The model also has rich predictions for labor market flows. Abowd and Zellner (1985) and Poterba and Summers (1986) show that CPS data on labor market status are subject to misclassification error. They estimate the effect of misclassification error on measured labor market stocks and flows. While the effect of misclassification error is mostly negligible for the measurement of stocks, it is sizable for flows, especially between unemployment and nonparticipation. For the purpose of our analysis misclassification error is particularly important since its effect on labor market flows is larger for women. To address this issue, we introduce misclassification error in the labor market status outcomes of our model. In particular, we use the transition matrix estimated by Abowd and Zellner (1985), which is reported in Table 13 in Appendix B.[8]

Table 3 reports the calibration targets and the corresponding model outcomes. All the targets are matched exactly with the exception of EU flow rate for skilled workers and EE flow rates for female and unskilled workers. However, differences are very small.

5.2 Model's Implications for 1978

In addition to the targeted outcomes, the model has predictions for the gender wage gap and labor market flows by gender. In our framework, the gender wage gap arises only because of women's higher quit rates. High quit rates lower the value of a match formed with a female worker, especially for high skilled workers for whom the foregone surplus is larger. This mechanism generates a gender wage gap of 10% for unskilled workers and a gap of 12% for skilled workers. The corresponding values in the data are 65% and 72%, respectively as shown in Table 8.[9] Thus the model captures

[8]In addition to Abowd and Zellner (1985), we use the misclassification error estimates calculated by Poterba and Summers (1986), and compute a version of the model without misclassification errors. These results are presented in Table 14 in Appendix B. The Poterba and Summers (1986) misclassification errors are reported in Table 13.

[9]We define the gender wage gap as the difference between male and female wages as a fraction of male wages.

	Data		Model	
	Women	Men	Women	Men
Unemployment	0.052	0.034	0.052	0.034
LFP	0.468	0.788	0.468	0.788
Skill premium	1.37	1.44	1.452	1.484
EU Rate	0.010	0.009	0.010	0.009
EE Rate	0.95	0.98	0.96	0.98
	Data		Model	
	Skilled	Unskilled	Skilled	Unskilled
EU Rate	0.005	0.010	0.006	0.010
EE Rate	0.98	0.96	0.98	0.97

TABLE 3: Calibration targets and the corresponding model outcomes.

less than 20% of the gender wage gap in the data. The rest of the gap in 1978 is likely driven by other factors that we abstract from in our paper.

In our calibration, we targeted the EU and EE flow rates by gender and skill. Table 4 shows all the flow transition rates in the data in 1978 for men and women as well as the model's implications for these flow rates.[10] We also present the ratio of women's flow rates to men's to assess the model's performance in capturing gender differences in flow rates. The biggest gender differences are in flows involving nonparticipation. In particular, the EN flow rate is around 3 times higher for women than men and the UN flow rate is about 2 times higher. Interestingly, flows between unemployment and employment are very similar across genders and clearly not the main source of the gender unemployment gap. Our model matches these patterns very well. Specifically, the EN flow in the model is 2.6 times higher and UN is 1.6 times higher for women relative to men.

While the model does a good job in matching the relative magnitudes of flows by gender, it underpredicts the levels of UN, NU and NE flows. It is well-known that three-state search-matching models typically have difficulty matching the flow rates that involve participation, as discussed in Garibaldi and Wasmer (2006) and Krusell, Mukoyama, Rogerson, and Şahin (2011). Following this literature, we introduce misclassification errors into the model. We find that misclassification error has minor effects on labor force participation and unemployment rates, though it improves the model's fit of labor market flows substantially. (See Table 14 in Appendix B.) This confirms the importance of adjusting for misclassification error in three-state labor market models.

5.3 The Role of Varying Labor Market Attachment: Comparison of 1978 and 1996

As we have shown earlier, the gender unemployment gap virtually disappeared by the mid-80s. Our hypothesis is that the change in relative labor force attachment of men and women played an

[10]The table reports transition probabilities from the state given in the row to the state given in the column. For example, in 1978, the employment-to-unemployment (EU) transition rate was 0.010.

	Women				Men				Women/Men			
DATA 1978		E	U	N		E	U	N		E	U	N
	E	0.946	0.010	0.044	E	0.978	0.009	0.013	E	0.97	1.11	3.38
	U	0.244	0.474	0.282	U	0.304	0.561	0.134	U	0.80	0.85	2.11
	N	0.036	0.014	0.951	N	0.044	0.017	0.939	N	0.82	0.82	1.01
	Women				Men				Women/Men			
MODEL		E	U	N		E	U	N		E	U	N
	E	0.962	0.010	0.028	E	0.980	0.009	0.011	E	0.98	1.11	2.55
	U	0.306	0.557	0.137	U	0.342	0.573	0.085	U	0.90	0.97	1.61
	N	0.019	0.011	0.970	N	0.042	0.018	0.939	N	0.45	0.61	1.03

TABLE 4: Labor market flows in 1978 and the model outcomes.

important role. To quantitatively assess the role of this factor, we select a new target year in the 90s. We choose 1996 as a new reference year for various reasons: 1. The aggregate unemployment rate in 1978 and 1996 are almost identical; 2. Both 1978 and 1996 are the mid-points of expansions; 3. Female labor force participation flattened out in mid 1990s (Albanesi and Prados, 2011); 4. The average years of schooling for women caught up with men's in the mid-1990s.

We first change parameters that reflect the variation in outcomes that are exogenous to our model: skill distribution, skill premium, and EU transition rate. We then readjust labor force attachment to match to the participation rates by gender in 1996 and evaluate the implications of the model for the gender unemployment gap. Specifically, we change the skill composition by gender to match the 1996 skill distribution. To incorporate the effects of the rising skill premium, we set productivity differences between high and low skill workers to match the aggregate skill premium. In addition, we vary δ_{ij} to match EU transition rate by gender and skill. Finally, to match the participation rates by gender in 1996, we change the upper bound of the support of the distribution of the opportunity cost of work for women and men.[11]

Table 5 shows the unemployment and labor force participation rates by gender in the data and in the model for both 1978 and 1996. Our model matches both statistics for 1978 perfectly since it is calibrated to do so. For 1996, our strategy is to match the labor force participation rates by gender and examine the implications for unemployment. In the data the gap declined from 1.8 percentage points to 0.3 percentage points. Our model recalibrated to 1996 predicts a gender unemployment gap of 0.4 percentage points and thus accounts for almost all of the convergence in the unemployment rates. We also define a percentage gender unemployment gap by computing the ratio of the unemployment gender gap to the aggregate unemployment rate, i.e. $(u_f - u_m)/u$, to take into account the changes in the aggregate unemployment rate. With this metric, the gender unemployment rate declines from 41% to 7.0% from 1978 to 1996 in the data while the model's prediction is a decline to 8.5%.

As we discussed above, the skill distribution, the skill premium, EU transition rates and labor

[11]See Figure 26 in Appendix B for the distributions of x by gender in 1978 and 1998.

	1978		1996	
Labor Force Participation Rate	Data	Model	Data	Model
Women	46.8%	46.8%	58.8%	58.8%
Men	78.8%	78.8%	76.3%	76.3%
Gap (ppts)	32	32	17.5	17.5
Percentage Gap	51.8%	51.8%	26.1%	26.1%
Unemployment Rate	Data	Model	Data	Model
Women	5.2%	5.2%	4.5%	4.9%
Men	3.4%	3.4%	4.2%	4.5%
Gap (ppts)	1.8	1.8	0.3	0.4
Percentage Gap	41%	41%	7.0%	8.5%

Table 5: Model outcomes for 1978 and 1996.

force attachment all changed from 1978 to 1996 in our model. In order to isolate the contribution of each factor, we change the corresponding set of parameters one at a time and examine their effects on the participation and unemployment gaps. These results are displayed in Table 6.[12] The third row of the table allows for changes in skill distribution, skill premium, EU transition rate jointly. This variant of the model, which does not allow for changes in attachment, predicts a gender gap of 0.9 percentage points for 1996 mainly through a rise in the male unemployment rate (see Table 14 in Appendix B). Table 6 also reports the outcome of the model where each factor is changed in isolation and shows that most of the convergence in the unemployment gender gap is accounted for by the increase in the male EU rate.[13] The change in the skill composition had a minor effect, consistent with our counterfactuals. The rise in the skill premium also had a small effect on the unemployment gender gap. The table shows that the change in labor force attachment is very important in explaining the evolution of the participation gap.

	Labor Force Participation Rate		Unemployment Rate	
	Gender Gap (ppts)	Gender Gap as a fraction of $lfpr$	Gender Gap (ppts)	Gender Gap as a fraction of u
1996 Data	17.5	26.1%	0.3	7.0%
Benchmark Model	17.5	26.1%	0.4	8.5%
EU,skill comp. and premium	29.6	45.1%	0.9	18.8%
EU	29.2	45.3%	1.0	20.4%
Skill composition	31.8	50.3%	1.6	40.0%
Skill premium	32.4	50.2%	1.7	41.5%

Table 6: Effect of different components of the model on the gender participation and unemployment gaps.

[12]Full set of results for both years are reported in Appendix B in Table 14.

[13]Table 14 in Appendix B shows the EU flow rates for 1978 and 1996. As can be seen, the EU flow rate increased from 1978 to 1996, especially for men.

	1978		1996	
	Data	Model	Data	Model
EN	3.38	2.55	1.80	2.08
EU	1.11	1.11	0.92	0.92
NU	0.82	0.61	0.84	0.74
NE	0.82	0.45	0.87	0.85
UN	2.10	1.61	1.58	1.45
UE	0.80	0.89	0.93	0.95

Table 7: Ratio of female flow transition rates to male transition rates in the data and the model.

Table 7 reports the female/male ratios of flow rates. The flow rates that involve nonparticipation displayed the largest degree of convergence in the data. Our model captures this feature of the data very well. The female/male ratio of EN flow rate drops from 3.38 to 1.80 while this ratio changes from 2.55 to 2.08 in the model. Similarly, UN flow rate also displays a sizable convergence both in the data and the model. NU and NE display limited convergence for the years we compare, however there is a general convergence pattern in the data that is captured by our model.[14]

	1978		1996	
	Data	Model	Data	Model
Unskilled	1.65	1.10	1.40	1.02
Skilled	1.72	1.12	1.49	1.01

Table 8: The gender wage gap in the data and the model.

Table 8 reports the model's implications for the evolution of gender wage gaps by skill. We find that gender wage gaps virtually disappear in the 1996 calibration of the model. This outcome is due to the fact that the rise in women's labor force attachment causes their quit rates to get closer to men's. Since quit rates are similar, the value associated to hiring male and female workers also converges, causing the gender wage gap to decrease. In the data, a substantial gender wage gap still remains, suggesting that the remaining gap is most likely due to other factors that we abstract from in our model. In Section 5.5, we consider alternative wage setting mechanisms.

5.4 The Effect of Attachment on the Unemployment Rate

Our quantitative analysis suggests that there is a link between the convergence of labor force attachment of men and women and the evolution of the unemployment gender gap. To understand

[14]Note that is all the NE flows in the model are driven by misclassification error since we do not allow nonparticipants to receive job offers. The rise in the female/male NE ratio is an artifact of the decline in the stock of nonparticipant women in the model.

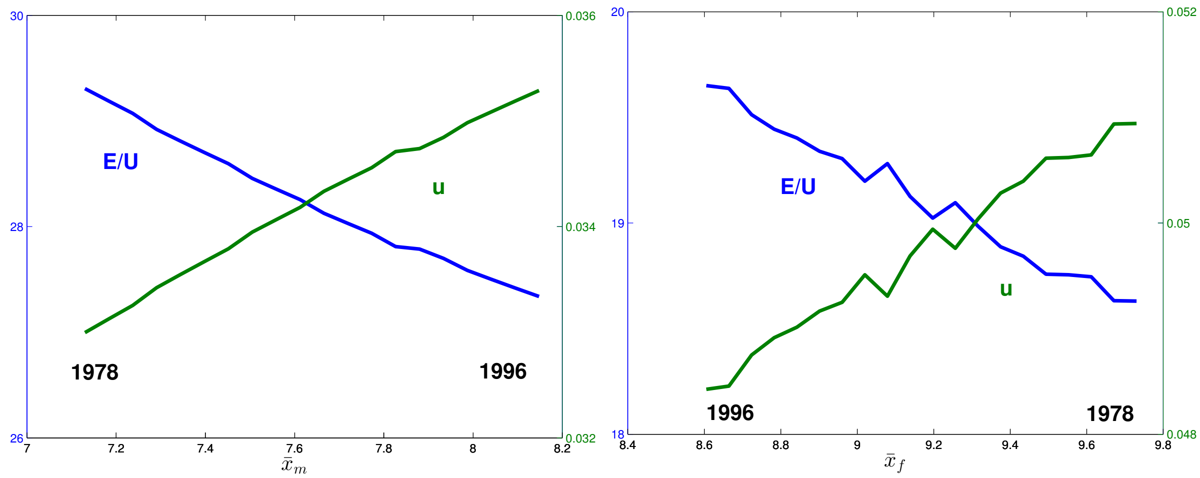

FIGURE 17: Employment-to-unemployment ratio and the unemployment rate as a function of $\bar{x}$ for men (left panel) and women (right panel).

the intuition behind our result, let us define the unemployment rate for gender j as

$$\frac{U_j}{U_j + E_j} = \frac{1}{1 + \frac{E_j}{U_j}}$$

where U_j and E_j are the number of unemployed and employed for gender $j = f, m$, respectively. This identity shows that the response of the unemployment rate to the change in labor force attachment depends on the response of the ratio E_j/U_j.

We illustrate the intuition focusing on the change in attachment for men. Recall that in our 1996 experiment, we change the upper bound of the support of the distribution of the opportunity cost of work to capture the effect of the change in attachment. For men, this implies an increase in the upper bound of the support to capture the decline in attachment. When this upper bound, $\bar{x}_m$ rises, there are more men in the population with higher opportunity cost of work. Consequently, the number of employed men, (E_m), declines. At the same time, the number of unemployed men, (U_m), also goes down since the value of being unemployed is lower due to the rise in the opportunity cost of work. As a result, both employment and unemployment go down for men causing a decline in male participation. What happens to the unemployment rate depends on the relative change in employment and unemployment. We find that in all variations of our model that we consider the employment effect dominates and E_m/U_m decreases with $\bar{x}$. The left panel of Figure 17 shows how E_m/U_m and male unemployment rate varies as $\bar{x}_m$ rises from its 1978 value to its 1996 value by simulating the model at 20 intermediate values. As the figure shows the unemployment rate increases as $\bar{x}_m$ rises since the decline in employment dominates the decline in unemployment. For women, since attachment rises from 1978 to 1996, the opposite happens and the unemployment rate goes down as employment rises more relative to the rise in unemployment as seen in the right panel of Figure 17.

5.5 Different Wage-Setting Mechanisms

In our baseline model, wages are determined through surplus splitting for males for each skill group. Then we impose that female wages are such that the surplus to a firm is equalized across genders. This mechanism endogenously generates gender wage gaps, within each skill group. In this section, we consider alternative wage-setting mechanisms and repeat our quantitative experiments for each case. In all these variations, we maintain the assumption that male wages determined through Nash bargaining and let the female wage setting vary. The cases we consider are:

1. *Nash bargaining*: wages are determined for men and women separately through surplus splitting within each skill group. Both men's and women's bargaining powers are set to the same value.

2. *Exogenous gender wage gap*: wages are determined for men through surplus splitting and the female wages are set such that gender wage gap is exogenously matched for each skill group.

3. *Different bargaining power*: wages are determined for men through surplus splitting and the female bargaining power is set so that the gender wage gap is satisfied for each skill group. The female bargaining power that matches the gender wage gap turns out to be 0.26.

We recalibrate our model for each of these three wage-setting mechanisms for 1978 and then carry out quantitative exercises to examine the implications of the model for the gender unemployment gap in 1996. All three models are calibrated in a similar fashion to the benchmark model with the exception of *different bargaining power* case, which target the gender wage gap using the bargaining power of women as a free parameter. Table 9 shows the implied unemployment gender gaps under different wage-setting mechanisms. All models generate very similar unemployment gender gaps for 1996 and explain the convergence in male and female unemployment rates. In all experiments, the unemployment rate is above its observed level. Recall that we do not target the unemployment rate in 1996, but only target the EU transition rate. Since the model does not match all the flow rates perfectly, most importantly UN transition rate, there is a discrepancy between the actual and model implies unemployment rates. Full set of results for these cases are reported in the Appendix B in Table 15.

	Unemployment Rate		Unemployment Gender Gap	
	Men	Women	ppts	as a fraction of u
1996 Data	4.2%	4.5%	0.3	7.0%
Benchmark	4.5%	4.9%	0.4	8.5%
Nash bargaining	4.6%	4.8%	0.2	4.5%
Exogenous gender wage gap	4.6%	4.7%	0.1	2.8%
Different bargaining power	4.6%	4.7%	0.1	2.2%

TABLE 9: Effect of different wage setting mechanisms on the gender unemployment gap.

The exogenous gender wage gap and different bargaining power specifications, by construction, match the gender wage gap by skill. However, for surplus splitting by gender this is not the case. As reported in Table 10 assuming surplus splitting in segmented markets by gender and skill generates a negative gender wage gap, implying a higher wage for women than men for each skill group. The reason is that since women's surplus conditional on the wage is smaller than men's, due to their greater opportunity cost of working, women have a higher outside option resulting in higher wages.[15]

	1978		1996	
	Data	Model	Data	Model
Unskilled	1.65	0.98	1.40	0.97
Skilled	1.72	0.98	1.49	0.96

Table 10: The gender wage gap in the data and the model with surplus splitting for men and women.

6 Cyclical Properties of Unemployment Rates by Gender

As we have shown in Figure 2, male unemployment has always been more cyclical relative to female unemployment rate. Despite the convergence of gender-specific unemployment rates, this pattern has not changed since 1948. We first investigate the whether these cyclical differences in unemployment rates by gender can be attributable to differences in industry distribution of men and women. Then, we study the role of the participation margin.

6.1 Industry Distributions

In Section 2, we calculated a counterfactual unemployment rate for women by assigning the male industry composition to the female labor force to isolate the role of industry distributions. Figure 18 shows both the actual and counterfactual rise in the female unemployment rates against the rise in the male unemployment rate by zooming in periods where the unemployment rate exhibited substantial swings. In particular, we start from the unemployment trough of the previous expansion and continue until the unemployment rate reaches its pre-recession level. For the 2001 and 2007-09 recessions, since the unemployment rate does not reach its pre-recession trough after the recession, we focus on a 12 quarter period for the 2001 recession and use all available data for the 2007-2009 cycle. We find that industry composition explains around half of the gender gap during the recessions.

We also use the Current Employment Statistics (CES), also known as the payroll survey, to compute the payroll employment changes during recessions and recoveries.[16] Since payroll employment data are available starting from 1964 by gender, we compute the employment changes starting

[15] For the same reason, assuming take-it-or-leave-it offers by firms will also result in a counterfactual prediction for the gender wage gap.

[16] For this exercise, we focus on 12 broad industry groups, while the unemployment rate counterfactual focuses on only 3 broad sectors.

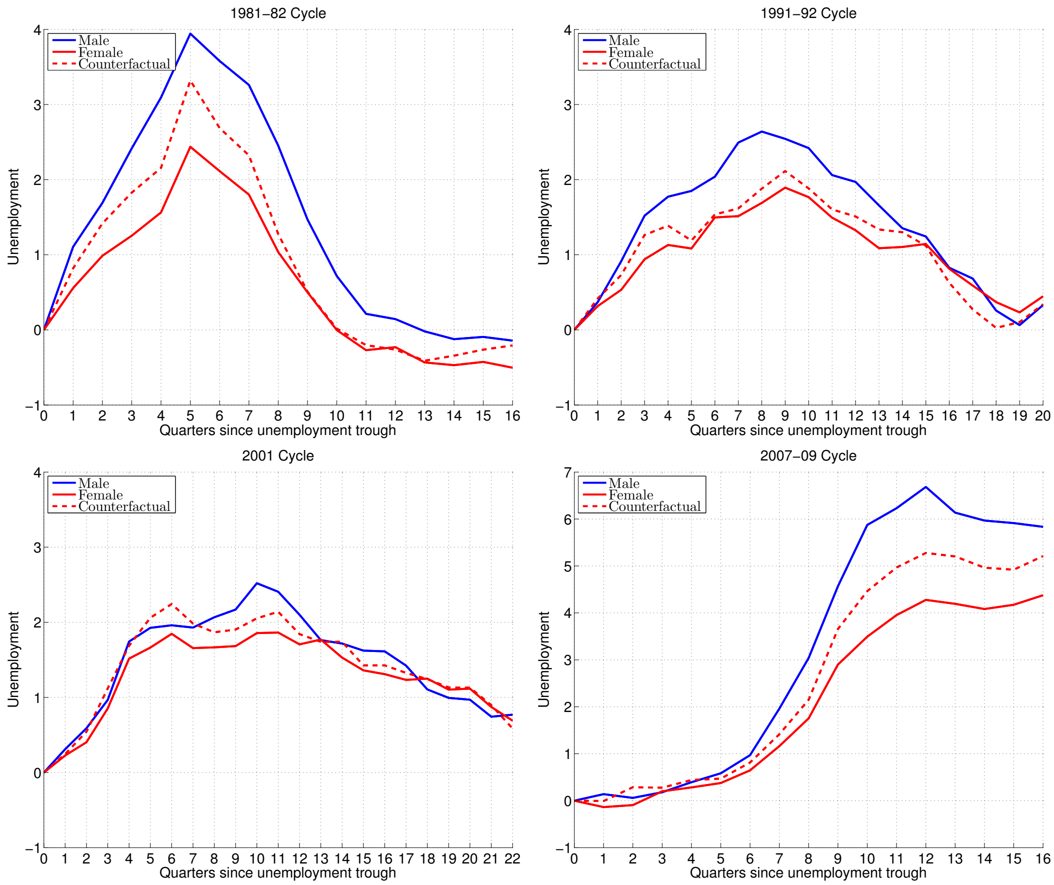

FIGURE 18: Counterfactual Unemployment Rates. Source: Bureau of Labor Statistics.

from 1969-70 cycle. For recessions, we report the percentage change in employment from the trough to the peak in aggregate unemployment for each cycle. For recoveries, we report the percentage change in employment from the peak to the trough in the aggregate unemployment rate except for the 2007-2009 cycle, for which we use all available data. As Table 11 shows, employment declines have always been higher for men than women. To isolate the effect of industry distributions, we assign the male industry distribution to the female labor force. For the last two recessions, the difference in industry distribution explains almost all the gender difference in payroll the employment change. For the 1981-1982 and 1991 recessions, it can explain approximately half of the gender difference, while for the earlier recessions it is mostly less important.

Table 12 reports the employment changes during recoveries. Up until the 1981-82 cycle, employment growth was much larger for women than for men in the recovery, despite the fact that men experienced larger job losses in the recession. This is a function of the sharp rise in female participation during this period. Assigning women men's industry distribution has virtually no effect on the resulting employment change. Women's participation stopped rising in 1993 (Albanesi and Prados, 2011). For the 1991 cycle, the change in employment in the recovery was approximately the same for men and women, whereas for the 2001 cycle it was slightly lower. For these two cycles, industry

Recessions	Men Actual	Women Actual	Women Counterfactual
12/1969-12/1970	-1.35%	+0.69%	-0.65%
10/1973-5/1975	-3.26%	+2.16%	-0.31%
5/1979-7/1980	-2.04%	+3.11%	-1.86%
7/1981-11/1982	-4.97%	-0.52%	-2.28%
7/1990-6/1992	-2.74%	0.81%	-1.70%
12/2000-6/2003	-3.16%	-0.72%	-4.72%
8/2007-10/2009	-8.34%	-3.28%	-7.47%

Table 11: Actual and counterfactual employment changes during recessions by gender.

Recoveries	Men Actual	Women Actual	Women Counterfactual
12/1970-12/1973	8.06%	14.12%	16.22%
5/1975-5/1978	9.31%	18.72%	20.83%
7/1980-7/1983	-2.84%	5.52%	4.11%
11/1982-11/1985	8.13%	14.42%	14.59%
6/1992-6/1995	7.92%	7.81%	7.04%
6/2003-6/2006	5.98%	3.38%	3.24%
10/2009-4/2012	5.17%	2.25%	0.77%

Table 12: Actual and counterfactual employment changes during recoveries by gender.

composition cannot explain the gender differences in employment growth. For the 2007-2009 cycle, women's employment grew by 2.25% during the recovery, whereas male employment rose by 5.17%. Assigning women the same industry distribution as men implies a counterfactual change in employment of 0.77% for women, suggesting that the recovery in employment for women would have been even weaker if they shared men's industry distribution.

6.2 The Participation Margin and Unemployment Rate Fluctuations

We use a simple decomposition to examine the relative roles of variation in employment and labor force participation in accounting for the fluctuations in unemployment:

$$\Delta u_t \approx \Delta log(L_t/P_t) - \Delta log(E_t/P_t)$$

where Δu_t is the change in the unemployment rate, $\Delta log(L_t/P_t)$ is the log change in the labor force participation rate, and $\Delta log(E_t/P_t)$ is the log change in employment-to-population ratio. Figures 19, 20, 21, 22, and 23 show the resulting decompositions for the last five business cycles. In each case, we start from the unemployment through of the preceding expansion and end three years after the unemployment peak. In the 1974-75 and 1981-82 recession, women continued to enter the labor force, maintaining the trend of that time. Thus we see, after an initial dip during these recessions, a rapid increase in the E/P for women in the recoveries. In the 1991-92 cycle, female participation was flat during the recession and grew modestly during the recovery, contributing to a rapid rise in women's employment growth in the recovery, relative to men. By contrast, in the 2001 and 2007-09 recessions—when the upward trend in female participation had stopped—female participation was roughly flat but dropped in the subsequent recoveries. Male participation in those recessions displayed similar declining patterns as in the previous business cycles. In the current cycle, the E/P ratio for women has continued to fall in the recovery, while those for men have stabilized. Therefore, even though the female unemployment rate did not rise as much during the recession as did the male rate, it has declined very little in the recovery so far.

These figures suggest that employment always declined less and unemployment grew less for women than men during recessions. The different behavior of women's employment and unemployment are tied to participation. In the 1974-75 and 1981-82 cycles, participation rose strongly for women during the recession, resulting is a a smaller decline in employment relative to men. In subsequent cycles, women's participation experienced smaller declines than men's, contributing to a smaller decline in employment growth, but the gender differences were smaller than in the earlier cycles. Turning to recoveries, in the 1974-75, 1981-82 and 1991-92 cycles, participation and employment rose strongly during the recovery for women, with unemployment declining to pre-recession levels and employment rising below pre-recession levels at the end of the recovery. For men, participation continued to decline in the recovery. While unemployment attained pre-recession levels at the end of the recovery, employment continued to be below pre-recession levels. For the 2001 and 2007-2009 cycles, participation declined during the recovery by more in percentage terms for men relative to women. However, men experienced a greater decline in unemployment and faster growth in employment relative to women during the recovery, and a faster decline in unemployment. However, employment at the end of the recovery was closer to pre-recession levels for women than for men.

The gender differences in participation and employment growth during recession and recoveries help explain the findings on the change over time in the role of industry composition, discussed in the previous section. Industry composition explains approximately half of the gender difference in employment growth in recessions for all cycles up until 1982. For these, we find strong within industry gender differences in employment growth during recessions, owing the rise in women's labor force participation. For later cycles, the gender difference in participation during the recession is much more muted, and within industry differences in employment growth virtually disappear, leading to a large role for industry composition. For early recoveries, the trend rise in women's participation boosts their employment growth, relative to men. For the 2001 and 2007-2009 cycles, women's participation declined during the recovery, similar to men. Since the counterfactual suggests that industry differences cannot explain the slower growth in women's employment relative to men for these recoveries, and gender differences in participation are small, the resulting gap must be due to within industry gender differences.

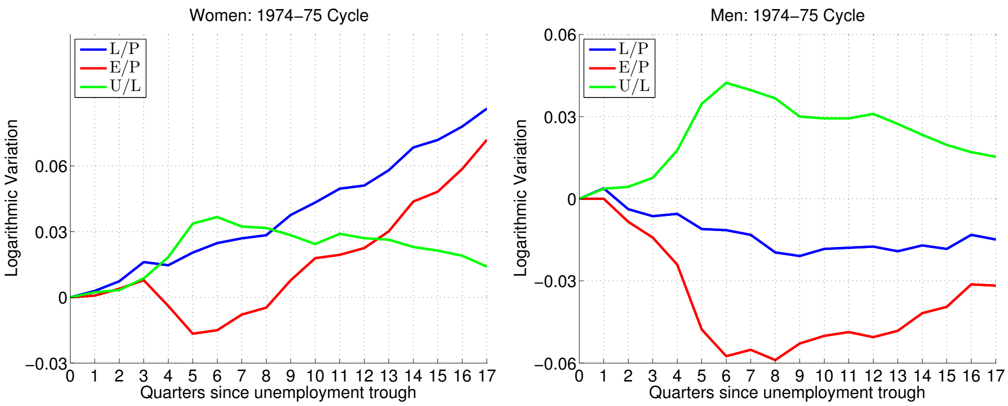

FIGURE 19: Decomposition of unemployment rate changes into changes in the labor force participation rate and the employment-to-population ratio for women (left panel) and men (right panel), 19974-75 cycle. Source: Bureau of Labor Statistics.

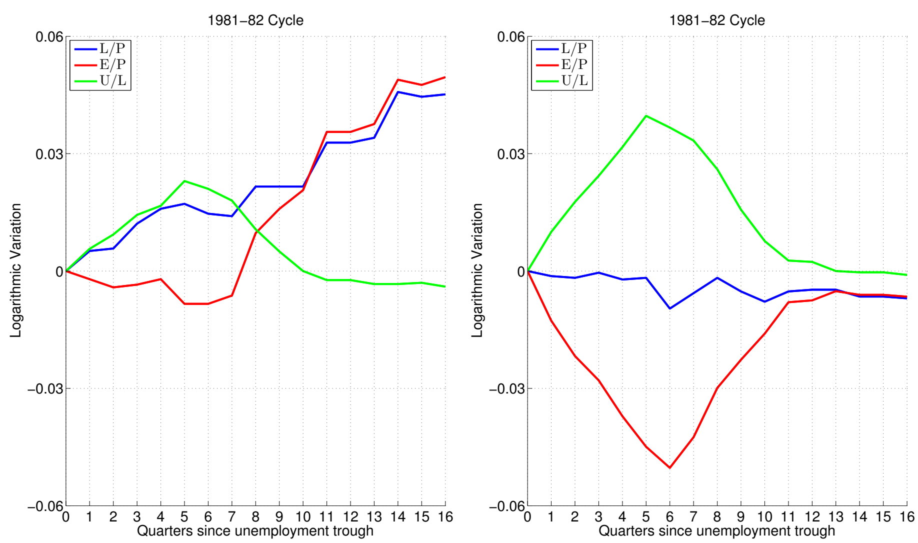

FIGURE 20: Decomposition of unemployment rate changes into changes in the labor force participation rate and the employment-to-population ratio for women (left panel) and men (right panel), 1981-82 cycle. Source: Bureau of Labor Statistics.

7 International Evidence

We conclude with an analysis of the international evidence on the link between labor force attachment and the unemployment rate. Female labor force participation has been rising in most advanced and emerging economies in the post-war period. Similarly, many countries experienced a modest decline in male participation. Given the convergence in labor market attachment, we should also expect gender unemployment gaps to close, based on the US experience.

We examine data on labor force participation and the unemployment rate by gender for a group of 19 advanced OECD countries, starting from 1970. Figure 24 displays the percentage gender gap in labor force participation, defined as $\frac{L_m - L_f}{L_m}$, and the percentage gender gap in unemployment,

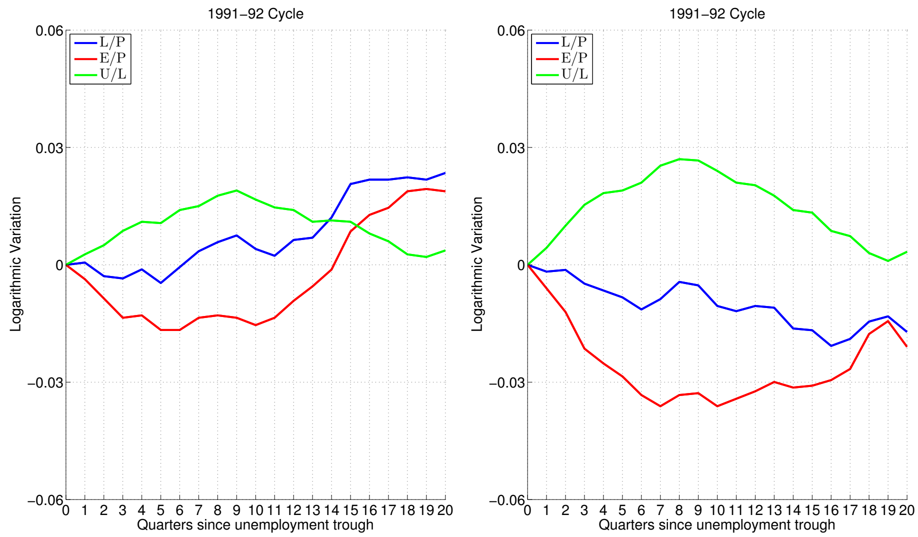

FIGURE 21: Decomposition of unemployment rate changes into changes in the labor force participation rate and the employment-to-population ratio for women (left panel) and men (right panel), 1990-91 cycle. Source: Bureau of Labor Statistics.

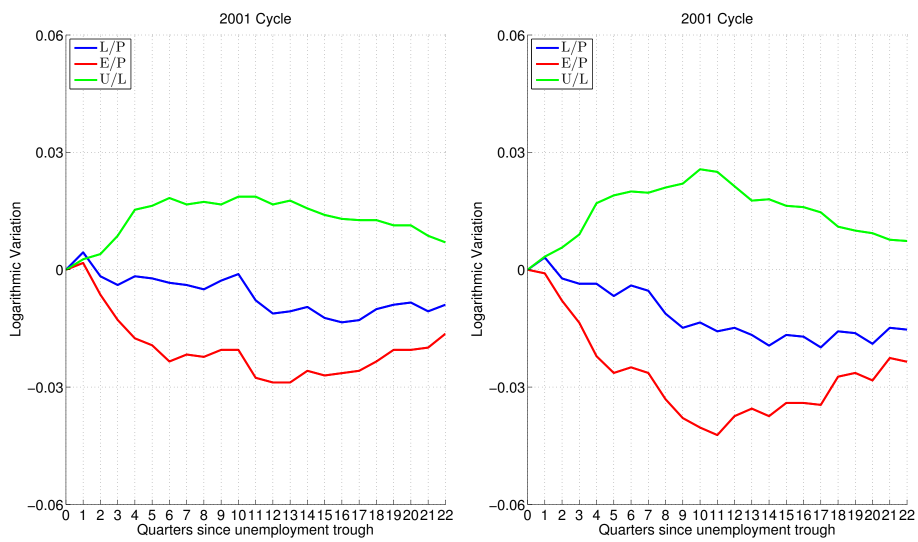

FIGURE 22: Decomposition of unemployment rate changes into changes in the labor force participation rate and the employment-to-population ratio for women (left panel) and men (right panel), 2001 cycle. Source: Bureau of Labor Statistics.

given by $\frac{u_f - u_m}{u_m}$. The countries are grouped based on language or geography. The top panel presents data for the English speaking group, comprising the United States, the United Kingdom, Canada, Australia, New Zealand and Ireland. For all these countries, except Ireland, the participation gap drops from around 40% in the early 1970s to around 15% in 2008, and the unemployment gap is close to zero starting in the mid-1980s. The US and Canada display a decline of the unemployment gap of approximately 30% in the preceding period. Australia displays un unemployment gap close to

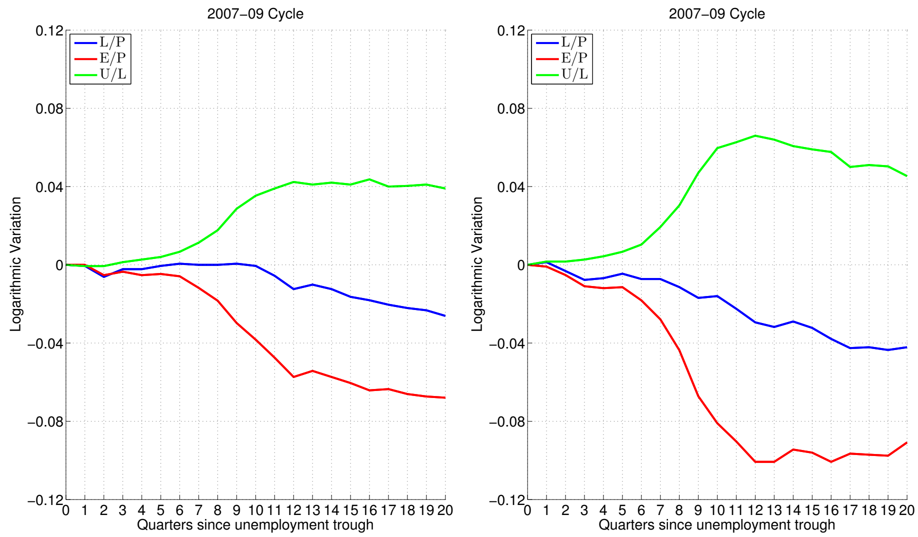

FIGURE 23: Decomposition of unemployment rate changes into changes in the labor force participation rate and the employment-to-population ratio for women (left panel) and men (right panel), 2007-09 cycle. Source: Bureau of Labor Statistics.

140% in 1970 from the early 1970s, and stabilizes close to zero by the early 1990s. By contrast, the unemployment gap is negative and sizable in magnitude for the UK, throughput the sample period. In Ireland, the participation gap is 65% in 1970, and falls to 23% by 2008. The unemployment gap peaks at 8% in 1985, and subsequently declines, reaching levels close to -20% after 2003.

The second panel reports data for the Nordic countries, which start from participation gaps between 25% and 40% in the early 1970s, converging to close to 5-10% by the mid-1990s, with most of the closing of the participation gap achieved by 1985. For Sweden and Norway the unemployment gap reaches zero in the late 1980s, following a period of sustained decline. Denmark displays a positive unemployment gap, with an average close to 30%, with little sign of convergence. In Finland, the unemployment gap starts negative, fluctuating between -25% and 0, before 1995, and follows a rising trend, becoming positive, but below 10%, after that.

The third panel displays data for continental European countries. The initial participation gap is typically larger in these countries, ranging from 45% to 65% in the early 1970s, dropping to values close 15% in 2008 for all countries except Luxemburg, where it reaches 25%. The behavior of the unemployment gap varies across countries. Belgium, France and Germany exhibit a strong closing of this gap, starting from initial levels of approximately 130%, 120% and 50%, respectively. In Germany, the unemployment gap settles around zero by 2002, while it is still around 30% in 2008 in Belgium and France, on a continuing downward trend. In Luxembourg, the unemployment gap starts from levels close to 100% in the late 1980s, and drops to approximately 35% by 2008. In the Netherlands, the gap rises from -40% in the early 1970s, to a peak of 80% in the late 1980s, before declining to values around 25% after 2003.

The fourth panel focusses on southern European countries, in which the initial participation gap ranges from 48% to 65%, reaching values between 25% and 30% by 2008, for Italy, Spain and Greece, and close to 20% for Portugal. The unemployment gap rises in the initial phase of the sample for all these countries, and then declines to varying degrees in the later phase. In Italy, the unemployment gap rises from 45% to165% between 1970 and 1977, and declines to approximately 55% by 2008. In Portugal, the unemployment gap rises sharply from 90% in 1974, to 300% in 1981,and then drops, settling to values close to 30% from the early 1990s.

These figures suggest two clear patterns. Countries with relatively low gender participation gap in the 1970s display a monotonic decline of the gender unemployment gap over the sample period, with the unemployment gap settling on values close to zero as the participation gap stabilizes. This pattern applies to the English speaking countries (except for the UK and Ireland), for the Nordic countries, and for the continental European countries, except for the Netherlands. In countries with relatively high initial participation gap instead, the unemployment gap tends to first rise, sometimes sharply, and then fall. This pattern prevails in the southern European countries and the Netherlands.

Do these different patterns reflect fundamental differences in labor market structure and culture, or do they reflect different stages of development? Of course, institutional and cultural differences likely play a large role in determining the size of the gender participation gap and the level of unemployment rate. Differences in the age structure of the population and fertility may also play a salient role (Sorrentino, 1983). But the experience of the US suggests that the initial rise in the gender unemployment gap is a consequence of an increase in the growth of female labor force participation. Figure 25 plots the gender unemployment gap and female labor force participation for the countries that display an initial rise in the gap, starting in 1960 or at the earliest available date, in addition to the US.[17] The figure clearly shows that the rise in the gender unemployment gap is associated to an initial acceleration in the rise in female labor force participation. A similar pattern prevails in the US, where the gender unemployment gap rises throughout the 1960s, as the growth in labor force participation accelerates.

The rising gender unemployment gap associated with the initial fast growth in female labor force participation in the US is driven by the low levels of labor market experience and relatively young age of the women newly entering the labor force, as well as by the fact that more married women enter, who tend to have low labor market attachment relative to the unmarried women who have historically been prevalent in the female labor force (Goldin, 1990). This pattern is consistent with the dynamics of the gender wage gap over the same period, which temporarily increased due to the dilution of skills and experience associated to with the new female entrants (O'Neill 1985, Smith and Ward 1989, O'Neill and Polacheck 1993). Likely, a similar pattern prevailed in other countries and we plan to investigate this in future research.

[17]For the US, we use monthly BLS data, smoothed with a 12 month centered moving average.

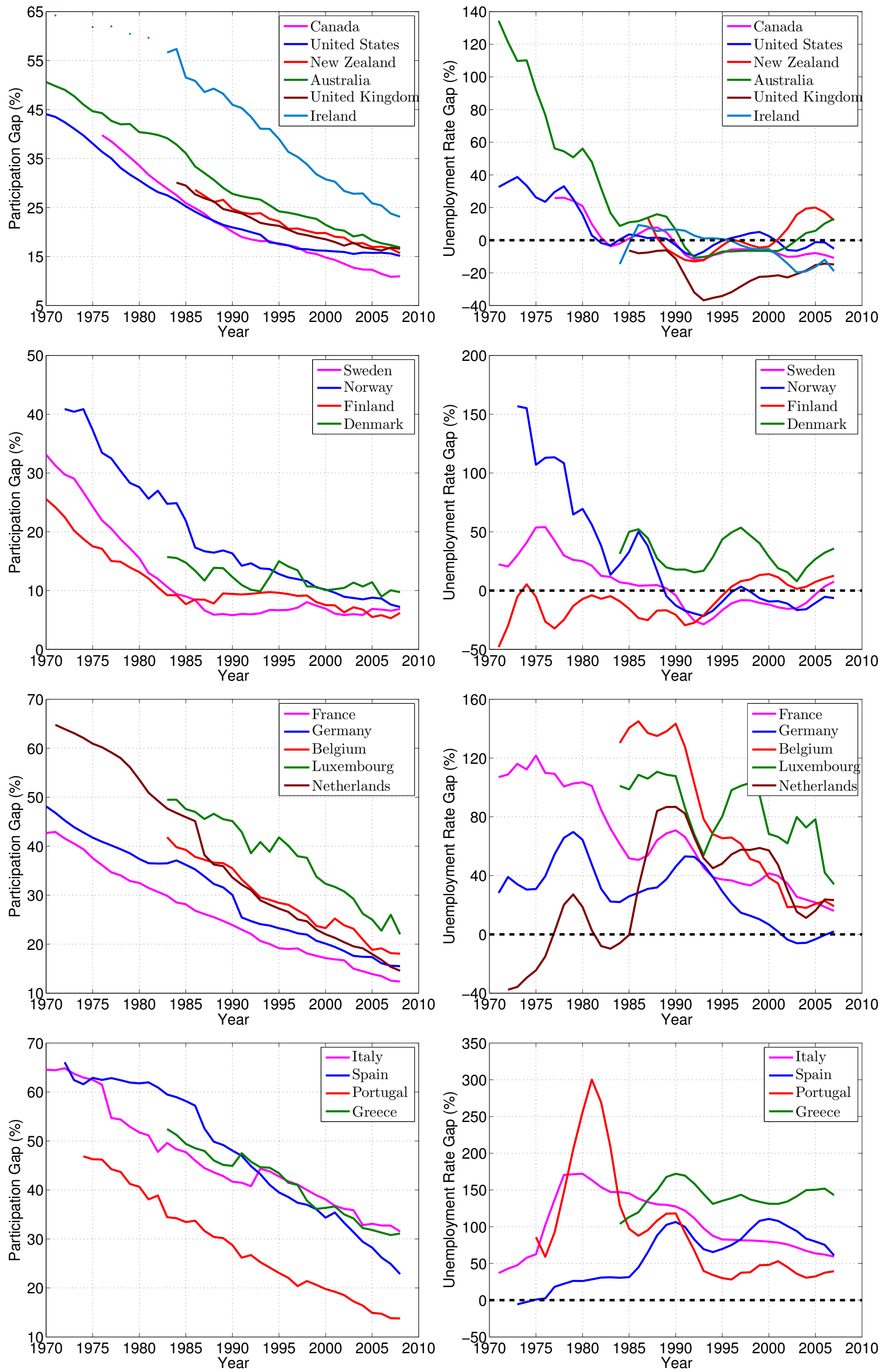

FIGURE 24: *Participation Gap* $= \frac{L_m - L_f}{L_m}$, *Unemployment Gap* $= \frac{u_f - u_m}{u_m}$. Source: OECD.

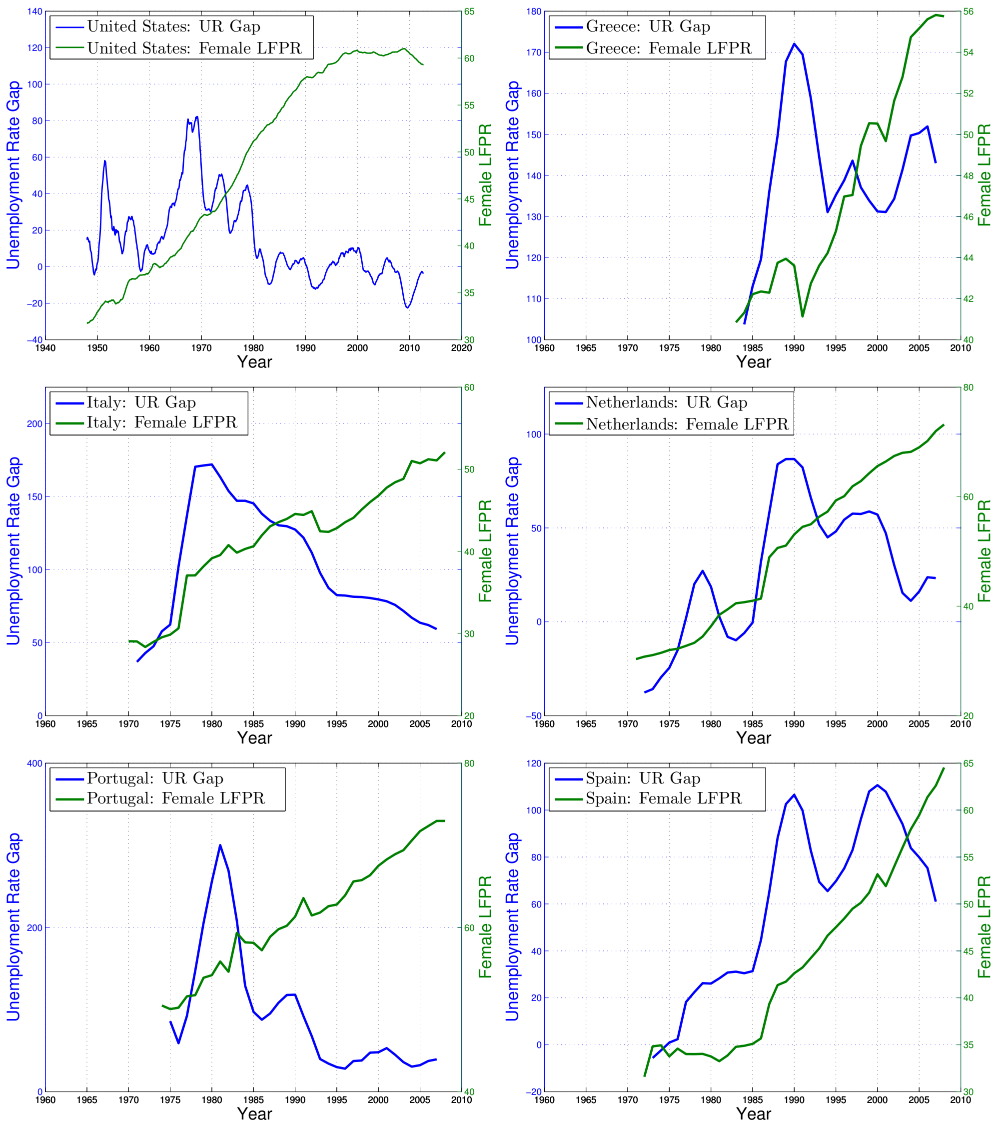

FIGURE 25: Female Labor Force Participation, *Unemployment Gap* $= \frac{u_f - u_m}{u_m}$. Source: BLS and OECD.

8 Concluding Remarks

We study the determinants of gender gaps in unemployment in the long run and over the business cycle. We show that while the trend component of unemployment has converged by gender over time, the cyclical component has remained stable. We attribute the closing of the gender unemployment gap to the convergence in labor market attachment of women and men and assess the contribution of this force with a calibrated three-state search model of the labor market. We take 1978 as the base for our calibration, then recompute the model for 1996 by allowing for variation in the gender differences in the opportunity cost of being in the labor force to match participation rates by gender in that year. We also adjust parameters that reflect the variation in outcomes that are exogenous to our model, such as the gender-specific skill distribution, the rise in the skill premium, and the rise in men's job-loss rate relative to women. We find that our model recalibrated to 1996 accounts for almost all of the convergence in the unemployment rates by gender in the data. The change in labor force attachment and the variation in the job-loss rate account for almost all of this convergence. Other exogenous factors have only a minor effect on the closing of the gender unemployment gap. We also examine the determinants of the cyclical behavior of unemployment by gender empirically, and find that industry composition plays an important role in explaining gender differences in employment for recent recessions, while in early recoveries gender differences in the behavior of participation can explain within industry gender differences in employment. Industry composition does not account for gender differences in employment behavior during recoveries. We show that the behavior of women's employment during recoveries is tied to the behavior of participation, while this relation is more tenuous for men. Evidence from advanced OECD economies suggest that the convergence in participation is associated with a decline in the gender unemployment gap for all most countries. Manning, Azmat and Guell (2006) have shown that cross-country variation in unemployment rates is mostly driven by differences in women's unemployment. Our findings suggest that this difference may in large part be due to differences in female participation.

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A Optimal Decision Rules and Worker Flows

The workers' optimal decision rules and corresponding workers flows depend on the relation between the cut-off values x_{ij}^a, x_{ij}^n, x_{ij}^q that define the reservation strategies. These three cut-offs can be ordered in six possible combinations, but only two cases are in fact possible under the assumption that $v_{ij}^W(\underline{x}_j) > v_{ij}^S(\underline{x}_j) > v_{ij}^N(\underline{x}_j)$ with $0 < s < e$:

- $x_{ij}^a < x_{ij}^q < x_{ij}^n$

The employment flows for this case are:

$$E_{ij,t+1} = E_{ij,t}(1-\delta_{ij})\left[\lambda_{ij}F_j(x_{ij}^a) + 1 - \lambda_{ij}\right] + U_{ij,t}p_iF_j(x_{ij}^a), \tag{14}$$

$$\begin{aligned} U_{ij,t+1} &= E_{ij,t}(1-\delta_{ij})\lambda_{ij}\left[F_j(x_{ij}^n) - F_j(x_{ij}^a)\right] + E_{ij,t}\delta_{ij}F_j(x_{ij}^n) \\ &+ U_{ij,t}(1-p_i)\left[1-\lambda_{ij}+\lambda_{ij}F_j(x_{ij}^n)\right] + U_{ij,t}p\left[F_j(x_{ij}^n) - F_j(x_{ij}^a)\right] + N_{ij,t}\lambda_{ij}F_j(x_{ij}^n), \end{aligned} \tag{15}$$

$$\begin{aligned} N_{ij,t+1} &= N_{ij,t}\left[1-\lambda_{ij}+\lambda_{ij}(1-F_j(x_{ij}^n))\right] + U_{ij,t}\left[(1-p_i)\lambda_{ij}(1-F_j(x_{ij}^n)) + p_i(1-F_j(x_{ij}^n))\right] \\ &+ E_{ij,t}\left[\delta_{ij}\left(1-F_j(x_{ij}^n)\right) + (1-\delta_{ij})\lambda_{ij}(1-F_j(x_{ij}^n)\right]. \end{aligned} \tag{16}$$

The third equation can also be replaced by:

$$N_{ij,t+1} = 1 - E_{ij,t+1} - U_{ij,t+1},$$

since this relation must hold in every period.

The steady state stocks can be solved by first solving for E_{ij} as a function of U_{ij} from the equation for $U_{ij,t+1}$:

$$E_{ij} = \frac{U_{ij}p_iF_j(x_{ij}^a)}{1-(1-\delta_i)[\lambda_jF_j(x_{ij}^a)+1-\lambda_{ij}]},$$

$$U_{ij} = \frac{\lambda_{ij}F_j(x_{ij}^n)}{1 - A_{ij} - \left[(1-p_i)(1-\lambda_{ij}+\lambda_{ij}F_j(x_{ij}^n)) + p_i(F_j(x_{ij}^n) - F_j(x_{ij}^a)) - \lambda_{ij}F_j(x_{ij}^n)\right]},$$

where

$$A_{ij} = \frac{p_iF_j(x_{ij}^a)\left[(1-\delta_{ij})\lambda_{ij}(F_j(x_{ij}^n) - F(x_{ij}^a)) + (\delta_{ij}-\lambda_{ij})F_j(x_{ij}^n)\right]}{1-(1-\delta_{ij})[\lambda_{ij}F_j(x_{ij}^a)+1-\lambda_{ij}]},$$

and

$$N_{ij} = 1 - E_{ij} - U_{ij},$$

for $i = h, l$ and $j = f, m$.

- $x_{ij}^n < x_{ij}^q < x_{ij}^a$

The employment flows for this case are:

$$E_{ij,t+1} = E_{ij,t}(1-\delta_{ij})\left[\lambda_{ij} F_j(x_{ij}^q) + 1 - \lambda_{ij}\right] + U_{ij,t} p_i F_j(x_{ij}^q),$$

$$U_{ij,t+1} = E_{ij,t}\delta F_j(x_{ij}^n) + U_{ij,t}(1-p_i)\left[1 - \lambda_{ij} + \lambda_{ij} F_j(x_{ij}^n)\right] + N_{ij,t}\lambda_{ij} F_j(x_{ij}^n),$$

$$\begin{aligned} N_{ij,t+1} = {} & N_{ij,t}\left[1 - \lambda_{ij} + \lambda_{ij}(1 - F_j(x_{ij}^n))\right] + U_{ij,t}\left[(1-p_i)\lambda_{ij}(1 - F_j(x_{ij}^n)) + p_i(1 - F_j(x_{ij}^q))\right] \\ & + E_{ij,t}\left[\delta_{ij}\left(1 - F_j(x_{ij}^n)\right) + (1-\delta_{ij})\lambda_{ij}(1 - F_j(x_{ij}^q)\right], \end{aligned}$$

for $i = h, l$ and $j = f, m$.

B Quantitative Analysis

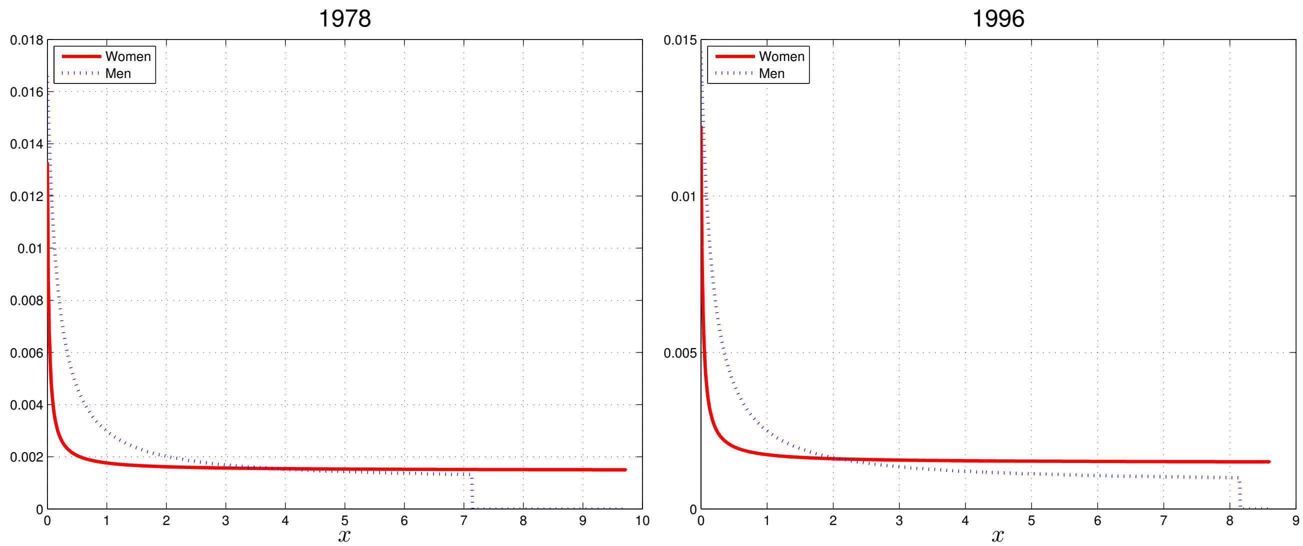

FIGURE 26: The distribution of x for men and women in 1978 (left panel) and in 1996 (right panel).

	Women				Men			
		REPORTED				REPORTED		
	TRUE	E	U	N	TRUE	E	U	N
Abowd and Zellner	E	0.9826	0.0020	0.0154	E	0.9916	0.0019	0.0065
	U	0.0147	0.8707	0.1146	U	0.023	0.899	0.078
	N	0.0042	0.0024	0.9934	N	0.0066	0.0041	0.9893
	Women				Men			
		REPORTED				REPORTED		
		E	U	N		E	U	N
Poterba and Summers	E	0.9811	0.0029	0.016	E	0.99	0.004	0.006
	U	0.038	0.794	0.168	U	0.031	0.899	0.07
	N	0.0106	0.0062	0.9832	N	0.0378	0.033	0.9292

TABLE 13: Misclassification probabilities estimated by Abowd and Zellner (1985) and Poterba and Summers (1986).

Note that P&S refers to the version of the model with misclassification error estimates based on Poterba and Summers (1986), no misc stands for the version of the model without misclassification error.

	1978 Data	1978 Model	1978 Model P&S	1978 Model no misc	1996 Data	1996 EU only	1996 Skill prem. only	1996 Skill comp. only	1996 EU, sk. prem. and comp.	1996 Model All
TOTAL										
Unemployment	0.044	0.044	0.044	0.045	0.043	0.049	0.041	0.040	0.048	0.047
LFP	0.618	0.618	0.618	0.624	0.671	0.644	0.645	0.632	0.656	0.671
E	0.593	0.593	0.593	0.598	0.643	0.614	0.622	0.609	0.627	0.641
EE	0.961	0.970	0.961	0.987	0.967	0.969	0.971	0.971	0.969	0.970
EU	0.010	0.010	0.010	0.008	0.011	0.011	0.009	0.009	0.011	0.011
EN	0.030	0.020	0.029	0.005	0.021	0.020	0.020	0.020	0.019	0.019
UE	0.272	0.323	0.325	0.293	0.271	0.309	0.346	0.340	0.327	0.323
UU	0.515	0.564	0.414	0.702	0.516	0.585	0.546	0.549	0.570	0.576
UN	0.213	0.113	0.260	0.005	0.213	0.106	0.107	0.111	0.103	0.101
NE	0.040	0.030	0.044	0.000	0.035	0.033	0.090	0.033	0.084	0.038
NU	0.015	0.015	0.029	0.008	0.017	0.017	0.017	0.015	0.020	0.017
NN	0.945	0.956	0.927	0.992	0.947	0.950	0.892	0.953	0.895	0.946
Skill premium	1.490	1.490	1.489	1.490	1.690	1.479	1.622	1.484	1.623	1.690
MEN										
Unemployment	0.034	0.034	0.034	0.034	0.042	0.044	0.032	0.032	0.043	0.045
LFP	0.788	0.788	0.788	0.792	0.763	0.797	0.815	0.799	0.811	0.763
E	0.762	0.762	0.762	0.766	0.731	0.763	0.791	0.775	0.778	0.730
EE	0.978	0.980	0.972	0.990	0.973	0.977	0.980	0.980	0.977	0.976
EU	0.009	0.009	0.009	0.008	0.012	0.012	0.009	0.009	0.012	0.012
EN	0.013	0.011	0.019	0.002	0.015	0.011	0.011	0.011	0.011	0.012
UE	0.304	0.342	0.334	0.295	0.282	0.322	0.369	0.359	0.343	0.331
UU	0.561	0.573	0.383	0.702	0.555	0.600	0.554	0.558	0.583	0.586
UN	0.134	0.085	0.283	0.002	0.163	0.078	0.077	0.083	0.074	0.082
NE	0.044	0.042	0.065	0.000	0.038	0.047	0.167	0.047	0.152	0.041
NU	0.017	0.018	0.043	0.009	0.019	0.021	0.024	0.018	0.029	0.019
NN	0.939	0.939	0.892	0.991	0.944	0.932	0.808	0.935	0.819	0.939
Skill premium	1.440	1.484	1.455	1.484	1.750	1.485	1.637	1.486	1.645	1.678
Wages, m.u.	-	2.666	2.682	2.666	-	2.662	2.674	2.661	2.660	2.648
WOMEN										
Unemployment	0.052	0.052	0.052	0.054	0.045	0.054	0.049	0.048	0.052	0.049
LFP	0.468	0.468	0.468	0.475	0.588	0.505	0.491	0.481	0.515	0.588
E	0.444	0.445	0.444	0.450	0.562	0.479	0.469	0.458	0.490	0.561
EE	0.946	0.962	0.951	0.984	0.962	0.962	0.963	0.962	0.963	0.965
EU	0.010	0.010	0.010	0.009	0.011	0.011	0.010	0.010	0.011	0.011
EN	0.044	0.028	0.038	0.007	0.027	0.027	0.028	0.028	0.027	0.025
UE	0.244	0.306	0.318	0.290	0.262	0.297	0.325	0.322	0.313	0.315
UU	0.474	0.557	0.442	0.703	0.480	0.572	0.540	0.541	0.558	0.566
UN	0.282	0.137	0.241	0.007	0.258	0.131	0.135	0.137	0.129	0.119
NE	0.036	0.019	0.026	0.000	0.033	0.021	0.021	0.020	0.023	0.035
NU	0.014	0.011	0.016	0.006	0.016	0.012	0.011	0.011	0.012	0.014
NN	0.951	0.970	0.957	0.994	0.951	0.966	0.968	0.969	0.965	0.951
Skill premium	1.370	1.452	1.457	1.452	1.600	1.454	1.546	1.459	1.588	1.700
Wages, f.u.	-	2.429	2.268	2.429	-	2.570	2.439	2.422	2.569	2.600

Table 14: Outcomes in the aggregate and by gender in the data and the model for 1978 and 1996.

	1978 Data	1978 Benchmark	1978 Exog. wages	1978 Both Nash	1978 Different γ	1996 Data	1996 Benchmark	1996 Exog. wages	1996 Both Nash	1996 Different γ
TOTAL										
Unemployment	0.044	0.044	0.043	0.044	0.043	0.043	0.047	0.047	0.047	0.046
LFP	0.618	0.618	0.618	0.618	0.617	0.671	0.671	0.671	0.671	0.670
E	0.593	0.593	0.593	0.593	0.592	0.643	0.641	0.642	0.641	0.641
EE	0.961	0.970	0.968	0.971	0.968	0.967	0.970	0.969	0.971	0.969
EU	0.010	0.010	0.010	0.010	0.010	0.011	0.011	0.011	0.011	0.011
EN	0.030	0.020	0.022	0.019	0.022	0.021	0.019	0.020	0.018	0.020
UE	0.272	0.323	0.345	0.309	0.343	0.271	0.323	0.348	0.313	0.346
UU	0.515	0.564	0.543	0.577	0.544	0.516	0.576	0.551	0.585	0.553
UN	0.213	0.113	0.112	0.113	0.112	0.213	0.101	0.100	0.102	0.101
NE	0.040	0.030	0.028	0.030	0.027	0.035	0.038	0.037	0.038	0.042
NU	0.015	0.015	0.015	0.014	0.015	0.017	0.017	0.017	0.016	0.017
NN	0.945	0.956	0.957	0.956	0.958	0.947	0.946	0.946	0.946	0.940
Unemp duration (mean)	2.746	1.785	1.862	1.744	1.854	3.854	1.756	1.855	1.727	1.838
Unemp. duration (median)	1.385	1.726	1.659	1.777	1.661	1.892	1.781	1.708	1.817	1.709
Skill premium	1.490	1.490	1.491	1.491	1.503	1.690	1.690	1.688	1.689	1.692
MEN										
Unemployment	0.034	0.034	0.034	0.034	0.034	0.042	0.045	0.046	0.046	0.046
LFP	0.788	0.788	0.788	0.788	0.789	0.763	0.763	0.763	0.763	0.763
E	0.762	0.762	0.762	0.762	0.762	0.731	0.730	0.730	0.729	0.729
EE	0.978	0.980	0.980	0.979	0.980	0.973	0.976	0.976	0.976	0.976
EU	0.009	0.009	0.009	0.009	0.009	0.012	0.012	0.012	0.012	0.012
EN	0.013	0.011	0.011	0.011	0.011	0.015	0.012	0.012	0.012	0.012
UE	0.304	0.342	0.329	0.348	0.327	0.282	0.331	0.313	0.330	0.308
UU	0.561	0.573	0.585	0.568	0.587	0.555	0.586	0.604	0.588	0.608
UN	0.134	0.085	0.086	0.084	0.086	0.163	0.082	0.083	0.082	0.084
NE	0.044	0.042	0.038	0.043	0.036	0.038	0.041	0.038	0.042	0.033
NU	0.017	0.018	0.017	0.019	0.017	0.019	0.019	0.018	0.020	0.018
NN	0.939	0.939	0.944	0.938	0.947	0.944	0.939	0.944	0.938	0.948
Unemp duration (mean)	2.746	1.763	1.720	1.778	1.713	3.854	1.725	1.671	1.722	1.656
Unemp. duration (median)	1.385	1.764	1.812	1.747	1.817	1.892	1.829	1.904	1.834	1.917
Skill premium	1.440	1.484	1.413	1.493	1.332	1.750	1.678	1.606	1.690	1.459
Wages, m.u.	-	2.666	2.681	2.671	2.686	-	2.648	2.662	2.645	2.665
WOMEN										
Unemployment	0.052	0.052	0.052	0.052	0.052	0.045	0.049	0.047	0.048	0.047
LFP	0.468	0.468	0.468	0.468	0.466	0.588	0.588	0.588	0.588	0.585
E	0.444	0.445	0.444	0.445	0.443	0.562	0.561	0.562	0.561	0.561
EE	0.946	0.962	0.958	0.963	0.958	0.962	0.965	0.962	0.966	0.962
EU	0.010	0.010	0.010	0.010	0.010	0.011	0.011	0.011	0.011	0.011
EN	0.044	0.028	0.031	0.026	0.032	0.027	0.025	0.027	0.023	0.028
UE	0.244	0.306	0.359	0.276	0.358	0.262	0.315	0.380	0.297	0.380
UU	0.474	0.557	0.506	0.586	0.507	0.480	0.566	0.504	0.582	0.504
UN	0.282	0.137	0.134	0.139	0.135	0.258	0.119	0.116	0.120	0.116
NE	0.036	0.019	0.019	0.019	0.019	0.033	0.035	0.036	0.034	0.050
NU	0.014	0.011	0.014	0.010	0.013	0.016	0.014	0.017	0.012	0.017
NN	0.951	0.970	0.968	0.971	0.967	0.951	0.951	0.948	0.953	0.933
Unemp duration (mean)	2.746	1.804	1.987	1.713	1.978	3.854	1.784	2.022	1.732	2.004
Unemp. duration (median)	1.385	1.692	1.524	1.804	1.523	1.892	1.737	1.530	1.802	1.521
Skill premium	1.370	1.452	1.356	1.498	1.566	1.600	1.700	1.704	1.697	1.959
Wages, f.u.	-	2.429	1.625	2.728	1.582	-	2.600	1.789	2.736	1.649

Table 15: Outcomes in the aggregate and by gender in the data and the models with different wage-setting mechanisms for 1978 and 1996.