Are We There?

Differences in Search, Preferences and Jobs between Young Highly Educated Male and Female Workers

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Abstract

Do young highly educated women face higher job search frictions, have stronger preferences for non wage job-specific amenities, and receive job offers entailing lower hourly wages or stronger wage penalties for amenities provision relative to men? I study a recent cohort of young, highly educated American workers, document the existence of a gender pay gap at the beginning of workers' careers, and provide evidence that its increasing path over years in the labor market can be rationalized by underlying unobservable differences in search frictions, preferences for amenities, and in the characteristics of the job offers that workers receive. Building on the descriptive evidence I collect, I answer the questions above by estimating a model of hedonic job search. I use the estimated parameters to show that young workers' predicted utility from jobs can be decomposed into components due to wage and wage penalties/gains for amenities provision in the job offers received, preferences for amenities, and workers' selection into different jobs. The main amenities of interest are flexible schedule, overtime, paid and unpaid parental leave, and child care. I find that young, highly educated male and female employed workers are remarkably similar in terms of both search frictions and preferences for job attributes, while female unemployed workers are less likely to obtain job offers than men, in spite of similar levels of labor market attachment. The job offers that women face, instead, differ from the job offers that men receive. Women tend to be offered low wages, and obtain lower wage gains attached to the provision of amenities relative to men. Wages and amenities-related wage penalties strongly affect the predicted male-to-female gap in utility that young workers obtain from jobs, especially in executive and professional careers. In addition, lower wage gains (or wage losses) that women experience when amenities are provided, tend to expand the gender wage gap in jobs providing benefits like flexibility and parental leave.

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1 Introduction

An extensive literature has documented many of the determinants of the wage gap between men and women[1], but residual gender wage differences remain even within groups of workers narrowly defined in terms of occupation (Goldin 2014) and firm (Card, Cardoso & Kline 2016). Moreover, while wages do not differ by gender at labor market entry, the pay gap expands by it may be plausible to imagine young women to *dislike* working long hours more strongly than men.

Finally, the observed wages of employed men and women can differ if workers receive inherently dissimilar job offers. Taking search frictions and preferences for amenities as given, women may be more likely than men to receive offers entailing lower wages and higher penalties for the provision of amenities. It is especially likely to happen if the underlying factors affecting their preferences for job attributes also entrench their mobility across jobs and employers (Manning 2003). To give an example, a labor market attached woman who knows she might give birth at some point in the future, may be somehow constrained to accept jobs offering some form of

fact suggests that it is unlikely that the lower rate of arrival of job offers to female unemployed workers is entirely driven by a potentially lower level of job search intensity among them.

Second, regarding preferences for non-wage attributes, I find that the utility from jobs is strongly affected by the provision of amenities for both young men and young women. Workers of both genders evaluate the provision of flexibility, parental leave and childcare positively, and would be willing to renounce to up to more than half of their current wages in order to obtain such benefits. In addition, both male and female workers evaluate overtime positively, suggesting that jobs requiring strong investments in work effort at the beginning of workers' career may also entail better future career prospects.

Differently from what one might expect, however, female workers are not necessarily more attached to certain job attributes than men, and parental leave is the only benefit that female workers appear to value substantially more than men. Interestingly, preferences for schedule flexibility are remarkably similar between men and women.

Finally, the distribution of job offers that female workers receive is very different from the male-specific job offers distribution. In most occupations and industries, young, highly educated female workers, are offered lower wages relative to men. Regarding the provision of amenities, the attribute that workers value the most, parental leave, is accompanied by wage gains for both men and women. This is consistent with the fact that, in an hedonic search framework, more productive firms offer higher wages and are more likely to offer non-wage benefits (Hwang, Mortensen & Reed 1998). Still, wage gains (losses) attached to the provision of all amenities tend to be higher (lower) for men than for women, especially when flexibility and parental leave are concerned.

When predicting the average utility that male and female workers with comparable ability obtain from jobs in different careers, I observe that the utility that workers get from employment relationships differs between men and women. In particular, women tend to obtain lower utility on average relative to men, and especially so in executive and professional careers. The discrepancy in wages offered across genders lowers women' s utility from jobs relative to men in a majority of cases. More importantly, in all careers, the higher wage gains attached to the provision of amenities in male-specific job offers tend to exacerbate the job-utility gap between male and female workers. This fact is especially relevant for workers in executive and professional careers, but affects workers in administrative careers as well. Hence, the main reason why female workers are sometimes observed to obtain higher utility than men, on average, is driven by the fact that, within certain careers, women are more likely than men to be employed in jobs providing utility-increasing amenities. The provision of amenities, however, comes at a cost in terms of the wages that female workers can achieve compared to men.

This paper is related to different strands of literature. First, by providing a comprehensive analysis of a recent cohort of male and female workers' early careers, I contribute to updating an earlier literature studying gender-based differences in wages and gains from job changes (Loprest 1992, Keith & McWilliams 1999), search frictions and their consequences (Bowlus 1997), and quit behavior (Light & Ureta 1992, Royalty 1998), among young US workers during the 1990s. Importantly, I incorporate in the analysis the fact that workers value non-wage job attributes (Mas & Pallais 2017), hence further expanding on the literature on early careers by modeling the possibility that male and female workers' labor market outcomes can also be affected by gender specificities in preferences over jobs. I do so by relying on the theoretical and methodological insights coming from the structural empirical hedonic literature (Dey & Flinn 2005, Flabbi &

Moro 2012, Sullivan & To 2014, Sorkin 2018) and on the work by Bonhomme & Jolivet (2009) mostly.

To the best of my knowledge, only Bowlus & Grogan (2009) and Liu (2016) study gender differences in search, preferences and job offers received in an hedonic serach framework, focusing on preferences for part time jobs and on gender-based heterogeneity in employment attachment. Differently from them, I focus on male and female workers showing high levels of both education and labor market attachment, and on amenities that may be particularly relevant for workers willing to invest in their careers. In this sense, I aim at grasping whether differences in gender-specific labor demand (job offers) may help explaining the portion of the residual gender wage gap that does not seem to be ascribable to gender differences between workers in their labor market behavior. By highlighting that gender differences in the job offers that workers receive can exist even when male and female workers do not differ in terms of preferences, I provide some suggestive evidence that firm-specific wage setting practices may matter in explaining the residual gap in wages, a topic that has been explored in depth within the literature on monopsony and monopsonistic discrimination (Card, Cardoso & Kline 2016, Card, Cardoso, Heining & Kline 2018, Manning 2003).[5].

As a final remark, it is important to notice that analyzing gender differences in search frictions, preferences for amenities and job offer distributions jointly, and through the lens of a structural model, is crucial to estimate both preferences and search frictions correctly. Estimating preferences from reduced form analyses on the observed cross-sectional relation between wages and amenities would lead to a bias due to the unobserved wage-amenities correlation in the job offers that workers receive (Bonhomme & Jolivet 2009, Hwang, Mortensen & Reed 1998, Lavetti & Schmutte 2018). Such bias can be especially problematic when studying differences

2 Data

2.1 Sample

I use data from the National Longitudinal Survey of Youth 1997 (NLSY97), a nationally representative panel including 8984 young males and females between 12 and 16 years old as of December 31, 1996. The first round of the survey took place in 1997 and data are available until Round 17 (2015-16). The NLSY97 interviews took place yearly until 2011 and became biennial from then on.

(i.e. wages above 200$ per hour) or unreasonably high weekly hours worked (i.e. more than 112 hours per week, corresponding to 16 hours per day in a seven-days work week). Finally, I drop workers who report to be employed in agricultural occupations or in the military for at least one job-spell/year cell.

The final sample consists of employee-job spell-year cells. In some analyses that follow, I will only retain information about the first relevant job held by an individual per year. In those cases, the sample consists of employee-year cells.

As a final step, I define highly educated workers as all workers who obtain a bachelor degree no later than their 25th year of age. It is worth noting that this definition of highly educated workers causes the sample to be unbalanced in such a way that female workers represent about 57% of the entire sample. The unbalance between men and women is not driven strongly by male workers' active military service at young age, but rather by recent cohorts of males' under-representation among college graduates[7]. The unbalance between men and women is partially attenuated by the selection of the highly labor market attached individuals[8].

2.2 Sample Characteristics

The final sample only includes non African-American and non Hispanic workers in non agricultural and non military employee jobs, who obtain their bachelor degree by age 25, who enter the labor market by 2012 and who do not leave employment for 52 consecutive weeks by the fifth year spent in the labor market. The work history of these workers is reconstructed for at least in wages has already arisen.

Table 1: Sample Characteristics

	Males	Females	Diff.	Std. Error	Obs.
	(a) Time Invariant Characteristics				
Master degree by age 26	0.067	0.104	-0.037	0.020	752
Prospective PhD graduate	0.021	0.017	0.005	0.010	752
Marries by NLSY Round 17	0.680	0.698	-0.018	0.034	752
Age at first child birth	28.509	28.093	0.416	0.321	416
Changes employer by 5th year in labor market	0.537	0.521	0.015	0.037	752
Total number of jobs held	2.598	2.512	0.086	0.129	752
Total number of years in sample	8.704	8.413	0.292	0.122	752
Total number of weeks in sample	423.500	402.361	21.139	6.820	752
	(b) Time Changing Characteristics: First Year				
Age	24.226	24.340	-0.114	0.155	752
No more in education by first year	0.662	0.620	0.041	0.035	752
Enrolled in school at time t	0.146	0.165	-0.019	0.027	752
Bachelor degree by time t	0.713	0.778	-0.065	0.032	752
Has child by time t	0.027	0.059	-0.032	0.015	752
Employer j provides unpaid maternity/paternity leave	0.209	0.317	-0.107	0.032	740
Employer j provides paid maternity/paternity leave	0.322	0.483	-0.161	0.036	740
Employer j provides child care	0.072	0.098	-0.026	0.020	740
Employer j provides flexible schedule	0.397	0.383	0.014	0.036	740
Employer j number of employees	596.636	516.884	79.752	207.925	750
Average weekly hours worked at j	43.530	42.547	0.983	0.621	752
Hourly rate of pay at j (in 2005 Dollars)	15.703	16.012	-0.308	0.662	752
Total number of weeks employed in t	47.634	48.689	-1.055	0.535	752
Duration in years of employment spell	4.652	4.592	0.060	0.232	752
Duration in weeks of employment spell	214.713	212.163	2.551	12.419	752
	(c) Time Changing Characteristics: Last Year				
Age	31.942	31.767	0.176	0.129	752
No more in education by first year	0.662	0.620	0.041	0.035	752
Enrolled in school at time t	0.067	0.071	-0.004	0.019	752
Bachelor degree by time t	1.000	1.000	0.000	0.000	752
Has child by time t	0.448	0.509	-0.061	0.037	752
Employer j provides unpaid maternity/paternity leave	0.508	0.659	-0.152	0.036	737
Employer j provides paid maternity/paternity leave	0.477	0.543	-0.067	0.037	737
Employer j provides child care	0.099	0.114	-0.014	0.023	737

job on average (Panel (a)), it is plausible to imagine that workers select over time into jobs providing better and better contractual benefits, and that workers take into account the provision of such benefits when changing job.

Concerning wages, female workers earn as much as male workers at labor market entry (a \$16 hourly salary), and they work as many hours per week and as many weeks per year (Panel

Table 4: Yearly Continuous Weeks in Employment Status

education). These workers are the main sample of interest in all the analyses that follow. For comparison purposes, the sample in panel (b) includes *low education* workers, defined as workers who do not obtain a bachelor degree by Round 17 of the NLSY97 (year 2015/16). Both samples only include individuals who never leave the labor market for more than one year in any of the first five years on the labor market. For each individual in the sample I only consider the first job in chronological order held in a certain year.

The composition adjusted means are computed using the predicted log-wages of male and female workers estimated for cohort of labor market entry and gender specific cells through separate regressions for each year of experience. The experience-specific regressions are estimated using NLSY97 cross-sectional sampling weights. Specifically, let $f_i = 1$ if a worker is female and 0 otherwise. $y_{ji} = 1$ if i entered the labor market in year $y_j \in \{2000, \ldots, 2007\}$. w_{it} is individual i log wage (in 2005 \$) in year of experience $t \in \{1, \ldots, 10\}$. Then the log wage in year of experience t of an individual i of gender f_i belonging to cohort y_i is

$$w_{it} = {}_{0t} + {}_{1t} f_i + \sum_{j=2000}^{2007} {}_{jt}\, y_{ji} + \sum_{j=2000}^{2007} {}_{jt}\, y_{ji} f_i + {}_{ijt}$$

Where the subscript t indicates that a separate regression is estimated for every year of experience, so that coefficients of all variables are allowed to vary across years in the labor market.

Subsequently, the cohort-gender specific average log-wages are weighted using the ratio between the total number of weeks worked by each cohort-gender group and the total number of weeks worked by workers of a given gender[10]. The gender-specific composition adjusted mean wage in a certain year of experience is the weighted average log-wage in that year of experience computed across different cohorts of labor market entrants.

Figure 1 shows that, while female workers without a college degree tend to earn less, on average, than their male counterparts since labor market entry, the average wage of young men and women who graduate by age twenty-five is similar when workers enter the labor market. This is unsurprising given the results of the t-tests reported in Table 1. However, by the beginning of the third year on the labor market, male workers' average wage overcomes the hourly pay that female workers receive by 2 log-points. The gap expands until reaching a maximum of 14 log-points by the beginning of the tenth year on the labor market.

[10] I use these weights in order to smooth variations in log-wages by year of experience that may be due to macroeconomic conditions. As an example, since most workers in the sample enter the labor market around 2003, one may expect the log-wages to drop considerably in years of experience 4 and 5 due to the financial crisis and to the high share of workers who are in the labor market since four or five years at that time. The sample in this exercise is restricted to individuals not entering the labor market later than 2007 so that all workers in the sample can be observed potentially for ten years.

Figure 1: Continuously Employed Workers: Composition Adjusted Mean Log-Wages

(a) College Degree by Age 25 (b) At most Some College

National Longitudinal Survey of Youth, 1997. Workers who are continuously in employment by the fifth year on the labor market and who enter the labor market between 2000 and 2007.

3.2 Returns from Experience: Search Capital, General Human Capital and Labor Market Attachment

In what follows I provide evidence that search and job changes determine a non negligible portion of the early career gender wage gap by relying on the notion of returns to experience. Returns to experience can be interpreted as increases in wages over the life cycle of a worker due to accumulated *search capital* (Burdett 1978, Mortensen 1986), and *general human capital* (Becker 1964).

Search capital captures the notion that, in a dynamic search framework with random matching, wages increase over time as employed and unemployed workers receive job offers and accept to enter employment or to switch job as soon as the present value of the received offer exceeds of experience to the gender wage gap in early career is absorbed away once the decomposition is performed including controls for job changes, suggesting a non negligible role of potentially gender specific job search dynamics in the determination of early career gender wage gap.

Finally, I provide evidence that voluntary job changes bring stronger wage gains for male workers relative to their female counterparts, and I show that gender differences exist in factors motivating job changes.

3.2.1 Disentangling Returns from Experience from Labor Market Attachment

In this section I show that differences in returns to experience between male and female workers in my sample are not driven by differences in neatly defined levels of labor market attachmnet.

All estimated models include controls for years of tenure at current employer and its square, dummies for residence in South and in a Metropolitan Statistical Area, and three dummy variables controlling for whether, in a certain year, a worker has been working between 31 and 40 hours, between 41 and 50 hours, more than 50 hours per week on average. Models are estimated labor market entry, persist when comparing women and men who are alike in terms of labor market attachment.

3.2.2 The Contribution of General Human Capital and Search Capital to the Gender Wage Gap

Actual experience

variable) contribute negatively to the gap, we can see that the tenure and actual experience components of the gap virtually explain it entirely.

The *actual experience* component, measured as the sum between the *returns to experience* (i.e. wage structure) component and the *experience endowments* (i.e. differences in average amount of accumulated experience), explains almost 50% of the average gender gap emerging in the early career of the NLSY97 highly educated workers. Among the 5 log-points wage differences due to experience, about 80% is explained by different returns to experience between male and female young high skill workers.

In order to disentangle the contribution of general human capital from the contribution of search capital and gains from job change, in panel (b) of Table 6 I report the results of the decomposition that I perform controlling for the contribution of job changes to the gender wage gap. The estimated models include a variable counting the number of times a worker has changed job until present.

Table 6: Wage Gap Decomposition: Actual Experience Model

Finally, to the extent that workers preferences for amenities can be (at least partly) driven by underlying factors a□ecting workers' labor supply flexibility, including family constraints and mobility costs, it is not to be excluded that, due to these factors, women are o□ered lower wages and/or stronger wage cuts (or lower wage gains) associated to the provision of certain amenities.

3.2.3 Gender Di erences in Gains from Job Changes: Di erences in Returns to Search Capital

Having noticed that approximately 53% of the early career gender gap in pay gap among high skill workers can be explained by gender di□erences in returns to job changes, I estimate the average wage gains/losses from job change. Specifically, I am interested in observing whether men gain more or less on average from job changes than women, where gains are measured in terms of (log) wages; and to which extent returns to actual experience di□er between men and women once di□erent returns to job changes have been accounted for. Hence I estimate a model of the form

$$\begin{aligned} w_{it} = \quad &+ \ {}_1exp_{i;t\quad 1} + \ {}_2exp^2_{1;t\quad 1} + \quad change\_job_{i;t\quad 1} + \\ &+ \quad change\_job_{i;t\quad 1} \quad exp_{i;t\quad 1} + \quad change\_job_{i;t\quad 1} \quad exp^2_{i;t\quad 1} + x^0_{i;t\quad 2} \quad + "_{i;t} \end{aligned} \tag{3}$$

Where change_job is an indicator variable taking value 1 for workers who changed job between t 2 and t 1. $"_{it} = \ _i + u_{it}$ where $_i$ is an individual specific fixed e□ect and u_{it} is an error term orthogonal to the regressors.

The parameter of interest, , indicates the di□erence in the expected value of the year t hourly wage between workers who accumulated the same amount of actual experience until t 1 and who di□er according to whether they started a new job in year t 1 or not. Similar models of gains from job changes were estimated by Del Bono & Vuri (2011).

The use of lagged regressors in model (3) is due to the fact that, while mobility decisions can be motivated by a wage o□er superior to the wage received at current employer, at the beginning of the career workers mobility choices can also be motivated by faster wage growth prospects. That is, workers can decide to accept an o□er whose initial wage is equal (or lower) relative to their current wage, but that rises faster over time. This view is not inconsistent with search models and can also be modeled in a search dynamic framework (Burdett & Coles 2003).

While the sign and magnitude of the estimated ^ and di□erences in it between male and female workers are of interest, the OLS estimated coe□cient cannot be given a *causal* interpretation due to unobserved di□erences in productivity between moving and non-moving workers, and because of bias due to self-selection.

Concerns regarding the unobserved ability bias can be attenuated estimating the model through fixed e□ect estimator. Dealing with self-selection is more complicated and requires to understand how the wage paths of workers who *decide* to change job would have evolved, had they remained at their previous job, relative to the wage paths of job stayers.

On the one hand, it is possible that workers who change job at t 1 would have experienced lower wage increases over time relative to *job-stayers* had they not moved, and that knowledge of this *flatter* counterfactual wage path motivated their decision to change job. In this case, the estimated ^ would represent a lower bound to the actual returns to job change.

Table 7: Returns to Job Change

	Baseline		Baseline with Controls		Compare to time t job changers		Compare to time t job changers with Controls	
	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Actual Experience=AE at (t-1)	0.0614	0.0607	0.0995	0.0717	0.0710	0.0664	0.1111	0.0811
	(0.0198)	(0.0258)	(0.0422)	(0.0528)	(0.0180)	(0.0256)	(0.0396)	(0.0520)
AE(t-1) Squared	-0.0009	-0.0005	-0.0019	-0.0014	-0.0020	-0.0009	-0.0029	-0.0015
	(0.0023)	(0.0030)	(0.0038)	(0.0054)	(0.0021)	(0.0030)	(0.0034)	(0.0053)
Change Job in t-1(I[Change(t-1)])	-0.1967	-0.0143	-0.2026	0.0334	-0.1805	0.0099	-0.1762	0.0726
	(0.1372)	(0.0681)	(0.1395)	(0.0686)	(0.1433)	(0.0862)	(0.1495)	(0.0754)
AE(t-1)*I[Change(t-1)]	0.0780	0.0342	0.1033	0.0288	0.0626	0.0323	0.0921	0.0321
	(0.0781)	(0.0395)	(0.0740)	(0.0406)	(0.0751)	(0.0446)	(0.0719)	(0.0449)
AE(t-1)Sqr*I[Change(t-1)]	-0.0036	-0.0048	-0.0071	-0.0047	-0.0020	-0.0048	-0.0063	-0.0058
	(0.0100)	(0.0052)	(0.0091)	(0.0054)	(0.0095)	(0.0056)	(0.0086)	(0.0059)
Change Job in T only(I[Change(t)])					0.0682	0.1182	0.1062	0.1652
					(0.1493)	(0.1728)	(0.1550)	(0.1522)
AE(t-1)*I[Change(t)]					-0.0664	-0.0378	-0.0535	-0.0388
					(0.0929)	(0.0918)	(0.0979)	(0.0867)
AE(t-1)Sqr*I[Change(t)]					0.0079	0.0037	0.0049	0.0026
					(0.0109)	(0.0105)	(0.0118)	(0.0103)
R^2	0.105	0.087	0.118	0.098	0.106	0.089	0.119	0.102
N	1932	2356	1932	2356	1932	2356	1932	2356
Controls	N	N	Y	Y	N	N	Y	Y

National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic highly educated workers who are

To corroborate this statement, in Table 8 I show that men' s returns to *search*-driven job changes are both economically and statistically significant, while gains from *search*-driven job changes are absent for female workers. In order to do so, I account for heterogeneity in the reasons why workers change jobs.

Table 8 shows that about 36% of both male and female workers' job changes are driven by workers' willingness to look for or take another job. Hence, only a third of job changes in the data can be neatly rationalized through the lens of a Burdett & Mortensen (1998) type model, and should lead to wage gains. Failure to account for this helps explaining the lack of statistical significance of men' s gains from job changes in Table 7. In addition, Table 8 shows that gender differences exist in reasons driving job changes that do not pertain to *job shopping*. While women who change job do so for family related reasons or pregnancy only 4% of the times, the difference relative to men changing job for the same reason (1%) is striking. Similarly, 11.5% of female workers job changes are due to transportation and mobility constraints, while only 7% of men' s job changes are due to the same motive. Finally, 6% of women' s job changes are driven by a lack of satisfaction with current work environment. The share of men' s job changes due to the same reason is only 3.6%.

To the extent that these types of mobility are not ascribable to a *job shopping* motives and that they are unlikely to be associated with wage gains (Manning 2003), they may explain why women do not experience either economically or statistically significant wage increases associated with job changes according to model (3). Furthermore, female and male workers who change job due to shopping motives (i.e. in order to increase their lifetime utility conditional on having received a job offer) are not necessarily equally likely to obtain a job offer and do not necessarily face the same set of outside options. This may reflect into different gains from job change among workers who change job in order to take or look for a different job.

In order to explore the relevance of these different channels, I estimate model (3) allowing for different reasons for job change. Heterogeneous returns from job change by mobility reasons are captured by the interaction between the appropriate mobility dummy variable and the actual amount of experience accumulated by a worker by the begin of the job held in year $t-1$.

Table 8: Reasons for Leaving Job

	Why Job Ended?				
	Males	Females	Diff.	Std. Error	Obs.
Layoff	0.058	0.044	0.014	0.014	1085
Plant closes	0.028	0.008	0.020	0.008	1085
Fired	0.024	0.024	-0.001	0.009	1085
End project	0.073	0.050	0.023	0.015	1085
Pregnancy or family	0.009	0.040	-0.032	0.009	1085
Look for other job	0.043	0.036	0.007	0.012	1085
Take other job	0.325	0.324	0.002	0.029	1085
School	0.064	0.042	0.022	0.014	1085
Transportation	0.069	0.115	-0.046	0.017	1085
Other legal or medical	0.024	0.023	0.001	0.009	1085
Dislikes working conditions	0.036	0.058	-0.022	0.013	1085
Other	0.006	0.011	-0.005	0.006	1085
Other unknown	0.242	0.225	0.017	0.026	1085

Specifically, let $change\_job\_reason_{k,i,t-1}$ be a dummy variable taking value 1 if a worker changed job between year $(t-2)$ and year $(t-1)$ due to reason $k \in \{1, \ldots, K\}$. The population model is

$$
\begin{aligned}
w_{it} = \; & + {}_1 exp_{i,t-1} + {}_2 exp^2_{i,t-1} + \sum_{k=1}^{K} {}_k change\_job\_reason_{k,i,t-1} + \\
& + \sum_{k=1}^{K} {}_k change\_job\_reason_{k,i,t-1} \; exp_{i,t-1} + \\
& + \sum_{k=1}^{K} {}_k change\_job\_reason_{k,i,t-1} \; exp1 +
\end{aligned}
$$

together with (t 2) occupational and industry class. The baseline set of control variables included in all models corresponds to the set of control variables in columns (3) and (4) of Table 7. The estimated model omits the interaction between the reason-specific job change dummies and the square of experience since a joint F-test rejected their significance in all models of Table 9. Heteroskedasticity and serial correlation robust standard errors are reported in parentheses.

Table 9: Returns to Job Change

	Baseline with Controls		Baseline with Year Dummies		Baseline with Year Trend		Baseline with more Controls	
	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Actual Experience=AE at (t-1)	0.1122	0.0754	0.0865	0.0843	0.1050	0.0780	0.0846	0.0916
	(0.0411)	(0.0533)	(0.1554)	(0.1163)	(0.1540)	(0.1170)	(0.1497)	(0.1211)
AE(t-1) Squared	-0.0036	-0.0021	-0.0033	-0.0025	-0.0035	-0.0021	-0.0027	-0.0023
	(0.0038)	(0.0055)	(0.0038)	(0.0058)	(0.0038)	(0.0057)	(0.0037)	(0.0057)
I[Change(t-1)]*Job *Destroyed* (D(t-2))	0.0131	0.1152	-0.0157	0.1159	0.0124	0.1153	0.0177	0.0769
	(0.1129)	(0.0849)	(0.1214)	(0.0894)	(0.1151)	(0.0861)	(0.1107)	(0.0884)
I[Change(t-1)]*Job Shopping(S(t-2))	-0.0858	0.0351	-0.1023	0.0365	-0.0863	0.0352	-0.0619	0.0214
	(0.0779)	(0.0712)	(0.0828)	(0.0725)	(0.0811)	(0.0708)	(0.0784)	(0.0902)
I[Change(t-1)]*Family Constraints(FC(t-2))	-0.8637	0.6874	-6.2675	0.6957	-0.9465	0.6881	-0.7543	0.6067
	(3.0672)	(0.3158)	(5.9018)	(0.3182)	(3.6567)	(0.3194)	(4.8894)	(0.3725)
I[Change(t-1)]*Dislike of Work Environment(WE(t-2))	-0.2611	0.0825	-0.3027	0.0597	-0.2624	0.0824	-0.3160	0.0783
	(0.4845)	(0.1187)	(0.4955)	(0.1138)	(0.4947)	(0.1169)	(0.4901)	(0.1363)
I[Change(t-1)]*Other Motives(O(t-2))	-0.2915	-0.0742	-0.2822	-0.0853	-0.2915	-0.0741	-0.2549	-0.0634
	(0.2554)	(0.1045)	(0.2404)	(0.1064)	(0.2559)	(0.1059)	(0.2481)	(0.1025)
I[Change(t-1)]*Mobility Constraints(MC(t-2))	0.0993	0.3370	0.0425	0.3341	0.0978	0.3370	0.0209	0.3209
	(0.2728)	(0.1356)	(0.2443)	(0.1380)	(0.2673)	(0.1357)	(0.2677)	(0.1347)
AE(t-1)*I[Change(t-1)]*D(t-2)	0.0500	-0.0343	0.0540	-0.0339	0.0498	-0.0343	0.0500	-0.0271
	(0.0425)	(0.0200)	(0.0426)	(0.0200)	(0.0416)	(0.0196)	(0.0434)	(0.0206)
AE(t-1)*I[Change(t-1)]*S(t-2)	0.0425	0.0075	0.0451	0.0061	0.0425	0.0075	0.0401	0.0113
	(0.0224)	(0.0170)	(0.0231)	(0.0176)	(0.0227)	(0.0171)	(0.0220)	(0.0216)
AE(t-1)*I[Change(t-1)]*FC(t-2)	0.1794	-0.1552	1.3564	-0.1564	0.1973	-0.1552	0.1534	-0.1362
	(0.6676)	(0.0685)	(1.2827)	(0.0672)	(0.7932)	(0.0686)	(1.0609)	(0.0808)
AE(t-1)*I[Change(t-1)]*WE(t-2)	0.0126	0.0136	0.0258	0.0169	0.0129	0.0138	0.0337	0.0163
	(0.0962)	(0.0451)	(0.0970)	(0.0459)	(0.0979)	(0.0447)	(0.0978)	(0.0532)
AE(t-1)*I[Change(t-1)]*O(t-2)	0.0652	0.0251	0.0627	0.0265	0.0651	0.0251	0.0583	0.0210
	(0.0503)	(0.0188)	(0.0467)	(0.0189)	(0.0497)	(0.0186)	(0.0480)	(0.0183)
AE(t-1)*I[Change(t-1)]*MC(t-2)	0.0357	-0.0707	0.0433	-0.0698	0.0361	-0.0707	0.0525	-0.0629
	(0.0627)	(0.0381)	(0.0584)	(0.0386)	(0.0621)	(0.0379)	(0.0639)	(0.0384)
R^2	0.127	0.104	0.138	0.109	0.127	0.104	0.145	0.116
N	1932	2356	1932	2356	1932	2356	1932	2356
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time Dummy	N	N	Y	Y	N	N	N	N
Time Trend	N	N	N	N	Y	Y	Y	Y
Occupation t 2	N	N	N	N	N	N	Y	Y
Industry t 2	N	N	N	N	N	N	Y	Y

National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic highly educated workers who are continuously in Employment by the fifth year of potential labor market experience. Models in columns (3), (4), (7) and (8) include controls for: whether a workers had obtained his/her Bachelor degree by time t 2, whether a worker was enrolled in school at time t 2, the log of weekly hours worked at t 1, years of tenure at time t 2 and its square, whether the workers had a union bargained contract at t 2, the log-number of employees as of t 2, whether employer j offered parental benefits and flexible schedule at t 2 and the number of out-of-the-labor-force gaps the worker experienced until t 2. In order to account for heterogeneity in macroeconomic condition at the time the job-change decision was made, the model includes a control for US region-specific unemployment rate at t 2.

The main coefficient of interest is the estimated ^$_k$ associated with the interaction between actual experience at the beginning of year (t 1) job and the dummy variable capturing job changes due to *shopping*. $_k$ captures the ceteris paribus difference in year t wages between two workers of the same gender who differ according to whether they stayed in the same job between year (t 2) and (t 1) or they changed employer due to job shopping.

The estimated coefficient is positive and statistically significant for highly educated young men, suggesting a 4 log-points wage difference at time t between time $(t-1)$ job shoppers and job stayers. The estimated coefficient is stable across specifications, and in particular it is virtually unaltered when the analysis is performed comparing job stayers and job movers within the same $(t-1)$ occupation and industry classes.

Although the shares of men and women who leave their employer to look for or accept another job are remarkably similar in the data, young female workers do not seem to experience any wage gain associated with job moves due to shopping. The estimated coefficient for them is always close to zero and statistically not significant.

Women who change job because of family or mobility constraints, or because of previous job *destruction*, instead, appear to lose relative to *job stayers*. This is not surprising in light of the literature on monopsony (Manning 2003). Moreover, since mobility constrained job movers and workers who lost their previous job are likely to experience out of work gaps between jobs, the lack of significant wage losses for both mobility constrained male workers, and for men who lost their previous job, is suggestive that the likelihood of receiving job offers when out of work is significantly lower for female workers relative to their male counterparts.

3.2.4 Gender Differences in Job Change Determinants

Search frictions, preferences for job attributes and the characteristics of the distributions of job offers that workers receive are, clearly, unobserved. Preferences for job attributes, however, can

$$y_{ijt} = I\left[j(t) \neq j(t+1)\right] = I\left[y^{*}_{ijt} \geq 0\right] \quad (6)$$

$$\Pr\left[y_{ijt} = 1 | z_{ijt}; \alpha_i\right] = \frac{\exp\{z'_{ijt}\beta + \alpha_i\}}{1 + \exp\{z'_{ijt}\beta + \alpha_i\}} \quad (7)$$

Where i indexed individuals, j refers to employers and t to calendar years. w_{ijt} is the logarithm of hourly wage earned at time t by individual i at job j, $I[\text{Parental Leave}_{ijt}]$ takes value 1 if employer j offers paid leave, unpaid leave or child care to i in t, $I[\text{Flexible Schedule}_{ijt}]$ takes value 1 if flexible schedule is available for i at employer j in year t. I am interested in observing whether the probability of job changes varies differently with wage and amenities between male and female workers. In order to account for other determinants of job change and potentially gender-specific search and mobility constraints, the models control for education, presence of children and marriage status. In addition, since mobility decreases with years since labor market entry, the model controls for a quadratic function of actual experience and years of tenure, and for the number of spells a worker spent out of the labor force. In order to account for labor demand factors, controls also include current occupation (9 categories) and industry (11 categories) dummies, union coverage, employer dimension and the US region-specific annual unemployment rate [14].

The conditional Logit model (Chamberlain 1980) solves the incidental variable problem due to the presence of unobservable individual-specific productivity differences potentially correlatated job-specific characteristics. In particular, the probability of job change decreses on average by 67% following a 1% incrase in wages for women, while it decreases by 41% for men. Also, the percentage change decrease in the probability of quitting a job when parental benefits are provided is more than 3 percentage points higher for women than for men. Finally, the average percentage change fall in the probability of job change when a flexible schedule is available relative to when it is not, is 37% higher for women than for men.

Table 10: Conditional Logit Models of Job Quit

	Males	Females
$I[Job(t+1) \neq Job]$		
Log-Hourly Wage in 2005 USD	-0.4120	-0.6739
	(0.1337)	(0.1492)
I[Parental Benefits Available at j]	-0.2879	-0.3213
	(0.0948)	(0.0951)
I[Flexible Schedule Available at j]	-0.4881	-0.6672
	(0.1592)	(0.1479)
Log-Number of Employees at Employer j	-0.0993	-0.0674
	(0.0489)	(0.0444)
First Child Born by t	-0.2192	-0.4727
	(0.2891)	(0.2534)
Married by t	-0.4815	-0.4655
	(0.2487)	(0.2077)
N	1632	1943
Controls	Y	Y

National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic highly educated workers who are continuously in Employment by the fifth year of potential labor market experience. Additional controls include the following individual and job (employer) specific characteristics at time t: a quadratic function of actual experience and years of tenure, (the log of) the number of weekly hours worked, a dummy indicating whether a worker has a union bargained contract, two dummies indicating whether a worker is married and has children respectively, two dummies indicating whether a worker has obtained his/her Bachelor degree and whether he/she is enrolled in formal education, 9 occupation and 11 industry dummies, the total number of spells out of the labor force, three dummies indicating whether the unemployment rate in the US region where the workers resides at t is medium-low, medium or high. The model is estimated on the subsample of workers who change at least one employer within five to ten years of labor market experience.

These results are of interest for two reasons. First, regarding the sensitiveness of the probability of job change with respect to job-specific amenities, Dale-Olsen (2006) points out (grounding on Gronberg & Reed (1994)), that in the Hwang, Mortensen & Reed (1998) hedonic search framework, a higher (lower) sensitiveness of the quit probability with respect to amenities suggests the existence of a higher (lower) marginal willingness to pay for amenities. In this contest, such result would suggest that young, highly educated and highly labor market attached female workers are nevertheless more willing than their male counterparts to trade-off wage increases with an improvement in job-related benefits and amenities.

Second, regarding the average wage elasticity of the probability of job change, Light & Ureta (1992) point out that, conditional on current experience, a lower (higher) average sensitiveness of quit with respect to wages may signal a higher ability to find more attractive outside labor market opportunities, conditional on one own current position. In this context, conditional on current wage and current experience, male workers may find it easier to search and find even better outside options than female workers, so that the average elasticity of quit probability with respect to wage is lower, in absolute value, for male workers than for female workers.

The body of evidence collected in this section shows two main things. First, even considering extremely similarly labor market attached and highly educated male and female workers, a gender wage gap arises early in workers' careers and expands, and more than half of the overall early-career wage gap is explained by gender specific wage gains and losses from job changes. Second, differences in wage returns from job changes may arise due to search frictions, to gender specific preferences for non wage job characteristics and to gender based differences in wage offers and in wage gains and losses associated to the provision of certain amenities.

In the next section I quantify the extent to which male and female workers differ in terms of search frictions, preferences, and job offers received in their early careers.

4 Hedonic Search Model

In this section I use the set up proposed by Bonhomme & Jolivet (2009) to estimate differences in preferences for amenities, search frictions and features of the job offer distributions between young, highly educated male and female workers.

In order to do so, I construct a monthly dataset containing individual and job-specific information covering the first five years spent on the labor market by the workers studied in the descriptive analyses. This can be done by exploiting the weekly arrays of the NLSY97 and by retaining, for each individual, information regarding the first week of each month in the sample. For workers who are employed in any given week, I can observe all the information of interest concerning the job that the worker performs and their employer. For workers who are not employed in a given week, I define the worker to be out of employment and implicitly assume the worker is unemployed. Observing weekly arrays and constructing a monthly dataset helps mitigating concerns regarding measurement error in transitions across employers and in and out of employment due to time aggregation.

Regarding workers and jobs, I keep information about wage and job or employer characteristics. The main amenities of interest are measured by dummy variables indicating whether parental leave (either paid or unpaid), child care and flexible schedule are (individually) available at current employer. In addition I allow workers to have preferences for long hours (average weekly hours worked at current job above 45). The inclusion of this additional control avoids that the estimated preferences for flexibility are confounded by gender differences in selection into jobs requiring overtime, suggested by evidence in Table 1.

Differently from the most sophisticated version of the model that Bonhomme & Jolivet (2009) propose, I do not model unobserved heterogeneity across workers of same gender, but I control for it by allowing for the possibility that both wage offers and workers' selection into jobs offering a certain amenity depend on workers' ability. Ability is measured using the (log of) the percentile of the CAT-ASVAB test score, available in the NLSY97. Furthermore, I allow wage offers and the likelihood of amenities provision to change depending on workers careers. In particular, I define four aggregate occupation classes and four aggregate industry class. Workers' careers are proxied by the occupation and industry in which workers are employed for the longest amount of time by the fifth year on the labor market. The occupation classes are defined as follows: the omitted group includes administrative, social services, education and health support workers; the *executive* class includes workers in managerial and executive careers; *professional* includes workers in professional specialty and legal occupations, *other* includes all remaining occupations. The four industry classes are: *education, administrative, health* (omitted); *finance*, *trade* and *other*.

Careers are defined in terms of time invariant characteristics for identification purposes. The definition of careers that I adopt implicitly assumes that workers choose their careers before entering the labor market, and that job markets are segregated by careers. Alternatively, I should have allowed job offers to differ by month-job specific occupation and industry and I should have allowed workers' preferences to be affected by time varying industry and occupation. If not, the estimation of the characteristics of job offers would have been confounded by unobserved workers' preferences for industry and occupation.

The set-up of the model is as follows. I assume that two separate labor markets exist for

Implying that the steady state share of unemployed workers is $U = q{=}(\ _0 + q)$ and the steady state share of employed workers is $(1 \quad U) = \ _0{=}(\ _0 + q)$.

Also, at steady state, the flow of workers into jobs yielding utility lower or equal to u must equal the flow of workers out of these jobs. Defining $G(:j car_{occ}; car_{ind}; b)$ the distribution of jobs across employed workers and $G_u(:j car_{occ}; car_{ind}; b)$ the observed distribution of utility levels, at steady state

$$
\begin{aligned}
{}_0 U F_u(u j:) + \ _2 F_u(u j:)(1 \quad U) G_u(u j:) &= q(1 \quad U) G_u(u j:) + \ _2 F_u(u j:)(1 \quad U) G_u(u j:) + \\
&+ \ _1 F_u(u j:)(1 \quad U) G_u(u j:)
\end{aligned}
\tag{10}
$$

It implies

$$
G_u(u j:) = \frac{F_u(w + \ ^0 a j:)}{1 + kF(w + \ ^0 a j:)}
\tag{11}
$$

where $k = \ _1{=}(q + \ _2)$, and

$$
\frac{g(w; a j:)}{g_u(w + \ ^0 a j:)} = \frac{f(w; a j:)}{f:}
$$

be affected by the amenities that a firm offers through the $(K \times 1)$ coefficient vector γ, that can only vary across genders. The second equation represents the factors affecting the provision of a certain amenity. The probability that a_k is provided may either increase or decrease in workers' ability and it can change depending on careers. This allows for the possibility that inherently heterogeneous workers select into jobs with different characteristics and that firms in different sectors may offer different contractual benefits.

Knowing the primitives of the model, the likelihood function can be written as in Bonhomme & Jolivet (2009). The normality assumption on the unobservables in the job offers allows to find a functional form for $f(w, a|\cdot)$ and $F_u(u|\cdot)$. Substituting the functional forms in (6) and denoting t_0 the first month of an observation in the sample, one can write the contribution of a worker in the t_0 cross-section of (w, a) as

$$l_{t_0} = \left(\frac{q}{\lambda_0 + q}\right)^{1-e_{t_0}} \left(\frac{\lambda_0}{\lambda_0 + q}\right)^{e_{t_0}} g_{t_0}(w_{t_0}, a_{t_0}|\cdot)^{e_{t_0}} \tag{16}$$

Where e_{t_0} $(1-e_{t_0})$ is an indicator for whether a worker is employed (unemployed) in month t_0.

For each $t \in \{t_0, \ldots, T-1\}$, the contribution of each person to the likelihood in the next period depends on time t transitions and can be written as

$$\begin{aligned} l_{t+1} = {} & q^{ju_t}[1-\lambda_0]^{uu_t} \\ & \lambda_0^{uj_t} f_{t+1}(w_{t+1}, a_{t+1}|\cdot)^{uj_t} \\ & [1-\lambda_1 \bar{F}(u_t|\cdot) - \lambda_2 - q]^{s_t} \\ & [\lambda_1 1\{w_{t+1} + \gamma' a_{t+1} > w_t + \gamma' a_t\} + \lambda_2]^{jj_t} f_{t+1}(w_{t+1}, a_{t+1}|\cdot)^{jj_t} \end{aligned} \tag{17}$$

The total contribution of an individual to the aggregate likelihood function comprising all months of all the first five years of labor market experience is

$$l(\cdot) = l_{t_0} \prod_{t=t_0}^{T} l_{t+1}(e_{t+1}, w_{t+1}, a_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, w_t, a_t, b, car_{occ}, car_{ind}) \tag{18}$$

Where $s_t, jj_t, ju_t, uj_t, uu_t$ are dummy variables indicating, respectively, workers who, between t and $t+1$: remain in the same job, change job, exit from employment, exit from unemployment, remain unemployed. These variables indicate that the value of $l_{t+1}(\cdot)$ depends on the types of transitions taking place between consecutive months.

Once the likelihood is written, the sequential maximum likelihood algorithm described by Bonhomme & Jolivet (2009) can be implemented to estimate the parameters of the wage offer distribution and the search and preference parameters. I estimate the model separately for men and women.

The likelihood function describing the joint density of (w, a) across N individuals over T months between the year of entry and the fifth year on the labor market is

$$L(:) = \prod_{i=1}^{N} l_{t_0;i} \prod_{t=t_0}^{T} l_{t+1;1}(e_{t+1}; w_{t+1}; a_{t+1}; s_t; jj_t; ju_t; uj_t; uu_t | e_t; w_t; a_t; b; car_{occ}; car_{ind}) \quad (19)$$

First, likelihood is divided in three parts: $L_1(\ )$, $L_2(\ ;\ ;\ )$, $L_3(\ ;\ ;\ )$, where   is the vector of all parameters of the unobserved job o er distribution F,   is the vector of search frictions parameters and   is the preferences parameters vector.

L

Panel (b) reports the estimated salary value of amenities. It corresponds to the minimum wage that a worker would accept for a job not providing an amenity as a fraction of the wage of a job offering the amenity and providing the same utility. Male workers would accept 44% of the no-amenities hourly wage in order to be provided flexibility. The figure is 43% for women. Also, 30% of the no-amenities hourly wages would be sufficient for women to accept a job entailing some form of either paid or unpaid parental leave, while 32% is the ratio for men.

Table 12: Estimated Marginal Willingness to Pay for Amenities

(a)	Parameters			
	f	h	l	c
	Females			
Coeff.	0.841	0.332	1.227	0.476
Asy.Std.Err.	(0.445)	(0.386)	(0.923)	(0.523)
LR Test p-Value	[0.000]	[0.480]	[0.000]	[1.000]
	Males			
Coeff.	0.814	0.663	1.146	0.671
Asy.Std.Err.	(0.740)	(0.649)	(1.015)	(0.892)
LR Test p-Value	[0.001]	[0.016]	[0.000]	[1.000]
(b)	The Utility Value of Amenities: e j			
	Flexibility	Long Hours	Parental Leave	Childcare
Females	0.431	0.717	0.293	0.621
Males	0.443	0.515	0.318	0.511

National Longitudinal Survey of Youth, 1997. Asymptotic Standard Errors in parentheses, Likelihood Ratio Tests p-Values in brackets. Each parameter likelihood ratio test is constructed by comparing the likelihood function estimated in the model to the likelihood function estimated when the specific parameter is constrained to be zero.

Workers' estimated preferences for amenities are strong for both genders. These results are consistent, in magnitude, with the preferences for other amenities estimated by Bonhomme & Jolivet (2009) on a sample of European men and, overall, provide evidence that workers' surplus from employment relationships is likely to be affected strongly by the contractual benefits offered. At the same time, the results do not support the idea that any observed difference in wages between male and female young and highly educated workers can be rationalized by large underlying difference27(vide3p2i6e94(y)27(e8uurplus)-238(from)-23bnTd [1ei-354(is)-3')-361(-3'361 Td [e8urr results show that male workers are able to select themselves into progressively better jobs, in terms of both wages and non wage benefits.

Concerning female workers, a significant wage premium is only associated to the provision of parental leave. Similarly to the evidence regarding male workers, it suggests that more productive firms are likely to offer both higher wages and amenities to their female employees. The parental leave premium, however, is not as high for female workers as it is for male workers.

distribution were characterized by the wage gains (or losses) associated to amenity provision in the estimated male job offer distribution.

Finally, the last element on the third row shows the contribution of amenities to the utility gap due solely to gender-specific subjective evaluations of amenities.

This simple exercise shows that the estimation of the structural search model outlined above allows to quantify the contribution of workers' characteristics (i.e. preferences) and of characteristics that pertain to the distribution of the job offers that men and women receive to workers utility.

The table below shows the results of the decomposition for workers at the 80th percentile of the CAT-ASVAB test in the more representative careers (administrative, executive and professional) in the administration, education, health and social services sector, and financial sector respectively.

Table 14: Predicted Utility Gap Decomposition

	(a) Administration, Education Health, Social Services			(b) Financial Services		
	Admin.	Executive	Professional	Admin.	Executive	Professional
Utility Gap	-0.406	-0.692	-1.089	0.052	-0.241	-0.572
			Utility Gap Components			
(1) Wage Offers	0.115	-0.062	-0.132	0.175	-0.002	-0.072
(2) Amenities Offers						
Through Wages	-0.536	-0.629	-0.623	-0.381	-0.511	-0.492
Through Preferences	-0.132	-0.120	-0.158	-0.118	-0.109	-0.148
(3) Selection	0.146	0.119	-0.176	0.377	0.381	0.140

The first line of the table shows that employed women are predicted to obtain lower utility from their jobs, on average, relative to men, unless they work in administrative careers in the financial sector. The remaining lines show the contribution of wage and non wage job attributes to the male-to-female expected utility gap.

Panel (1) shows that women in executive and professional careers obtain lower wage offers relative to men, while the opposite is true for administrative workers. The first line in Panel (2), however, shows that gender differentials in pay premia attached to the provision of amenities strongly contribute to the utility gap between young men and women in all careers. In executive and professional careers, the differential wage premia attached to the provision of amenities further exacerbates the male to female gender gap in the wage offers that workers receive. In administrative careers, a gender gap in wage offers arises when employers offer contractual benefits such as flexibility and parental leave. As the second line in Panel (2) shows, the slight gender differences in workers' subjective evaluation of amenities does contribute to the utility gap, but it is not the main force driving it. In addition, due to the similarity in preferences for contractual benefits between young men and women, the provision of contractual benefits does not appear to *compensate* female workers (relative to males) for the lower wage gains (or wage losses) that they incur as contractual benefits are provided. Panel (3), instead, shows that women' s over-representation in amenities-providing jobs attenuates the overall male-to-female

line with the recent work by Goldin, Kerr & Olivetti (2020).

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Appendix

A1. Detailed Dataset Construction

was employed in a given job. The identifier is employer specific, implying that a change of job consists of a change of employer. Since the firm identifier is only unique within individuals, it is not possible to observe whether two or more individuals are employed by the same firm. In the next section I will detail the procedure I followed to merge job-to-week specific information.

The job-specific information contained in the NLSY includes the day, month and year in which an employment relationship starts and ends. For ongoing jobs, in each interview the start date coincides with the end date as of the preceding interview, and the end date corresponds with the interview date. The survey also reports the hourly wage as of the interview date or at the time the employment relationship ended, the hourly compensation, the usual number of weekly hours worked, the actual number of weeks worked between two successive survey interviews, 4 digit occupation an industry codes, whether the worker is in an internship, whether he/she is self conducted, say, in 2016, the year is coded as 2015. Second, among the cases mentioned above, case a: represents the vast majority of non-merged week-job-specific data.

For data falling in case a:, for all weeks such that job-specific information could not be merged,

A2. Actual, Potential and Work History Experience

Table 15: Light and Ureta (1995) Experience Models Estimated Coefficients

	WH Males b/se	WH Females b/se	AE Males b/se	AE Females b/se	PE Males b/se	PE Females b/se
WH = Fraction of Year worked 1 Years Ago	0.1269	0.1512				
	(0.0393)	(0.0309)				
WH = Fraction of Year worked 2 Years Ago	0.1113	0.0487				
	(0.0356)	(0.0283)				
WH = Fraction of Year worked 3 Years Ago	0.0787	0.0891				
	(0.0353)	(0.0279)				
WH = Fraction of Year worked 4 Years Ago	0.0593	0.0443				
	(0.0356)	(0.0280)				
WH = Fraction of Year worked 5 Years Ago	0.1307	0.0696				
	(0.0366)	(0.0292)				
WH = Fraction of Year worked 6 Years Ago	0.0589	0.0774				
	(0.0385)	(0.0309)				
WH = Fraction of Year worked 7 Years Ago	0.0997	0.0742				
	(0.0409)	(0.0335)				
WH = Fraction of Year worked 8 Years Ago	0.0645	0.0702				
	(0.0440)	(0.0377)				
WH = Fraction of Year worked 9 Years Ago	0.0581	0.0557				
	(0.0512)	(0.0441)				
Years of Tenure	0.0027	-0.0188	0.0065	-0.0135	0.0093	-0.0064
	(0.0196)	(0.0162)	(0.0186)	(0.0155)	(0.0179)	(0.0150)
Years of Tenure Squared	-0.0031	0.0005	-0.0034	0.0001	-0.0033	-0.0004
	(0.0022)	(0.0018)	(0.0022)	(0.0018)	(0.0021)	(0.0017)
AE = Share of Time worked until present			0.1049	0.0851		
			(0.0174)	(0.0145)		
AE Squared			-0.0021	-0.0018		
			(0.0019)	(0.0016)		
PE = Years since labor market entry					0.0977	0.0737
					(0.0164)	(0.0136)
PE Squared					-0.0019	-0.0009
					(0.0017)	(0.0014)
Constant	2.3749	2.4081	2.3807	2.4277	2.3676	2.4183
	(0.0655)	(0.0484)	(0.0647)	(0.0477)	(0.0650)	(0.0477)
R-sqr	0.186	0.144	0.185	0.142	0.186	0.143
Region of Residence	Y	Y	Y	Y	Y	Y
Residence in MSA	Y	Y	Y	Y	Y	Y
Control for Interruptions	Y	Y	Y	Y	N	N
Control for hours	Y	Y	Y	Y	Y	Y

A3. Conditional Logit Job Quit Models: Estimating the Average Elasticity of the Probability of Job Change following Kitazawa (2012)

Given the Conditional Logit Model

$$
\begin{aligned}
y_{ijt} &= z_{ijt}^{0} \quad + \quad {}_{i} + u_{ijt} \\
&= \quad + \; w_{it} + \; I\,[\text{Parental Benefits}_{ijt}] + \; I\,[\text{Flexible Schedule}_{ijt}] + x_{ijt}^{0} \quad + {}_{i} + u_{ijt} \qquad (22)
\end{aligned}
$$

$$
y_{ijt} = I\,[j(t) \neq j(t+1)] = I\,[y_{ijt} \quad 0] \qquad (23)
$$

$$\Pr[y_{ijt} = 1 | z_{ijt}, \ _i] = \frac{\exp\{z_{ijt}^{0} \ + \ _i\}}{1 + \exp\{z_{ijt}^{0} \ + \ _i\}} \tag{24}$$

Table 16 reports the vector of estimated $\hat{}$. As shown by Chamberlain (1980) and Wooldridge (2002) $\hat{}$ is the vector of estimated partial effects of time varying characteristics on the log odds ratio of y_{ijt}.

Kitazawa (2012) shows that the conditional logit framework allows to estimate the average elasticity and semi-elasticity (depending on the definition of z_{ijt}) of $\Pr[y_{ijt} = 1 | z_{ijt}, \ _i]$ with respect to the independent variables, provided that the identifying assumptions of the Conditional Logit Model hold.

Following Kitazawa (2012), let $N \to \infty$ and T constant. The model in (23) and (24) can be rewritten as

$$y_{ijt} = p_{ijt} + u_{ijt} \tag{25}$$

$$p_{ijt} = \Pr[y_{ijt} = 1 | z_{ijt}, \ _i] \tag{26}$$

Now, =

p_{ijt} when z^k_{ijt} goes from 0 to 1 can be written as

$$\frac{p^1_{ijt} - p^0_{ijt}}{p^0_{ijt}} = (\exp\{\beta_k\} - 1)\frac{1}{1 + \exp\{z^0_{ijt}\beta + \alpha_i\}} \approx \beta_k (1 - p^1_{ijt}) \tag{30}$$

Where the last line holds because $e^{\beta_k} - 1 \geq \beta_k$ for all $\beta_k \in \mathbb{R}$, with equality when $\beta_k = 0$. Hence, $e^{\beta_k} - 1 \approx \beta_k$ for small enough β_k.

Hence, the conditional logit model allows to estimate consistently the mean percentage change in p_{ijt} due to changes in categorical variables as well.

Table 16: Conditional Logit Models of Job Quit

	Males	Females
I[Job(t + 1) $\neq$ Job]		
Log-Hourly Wage in 2005 USD	-0.4831	-0.7954
	(0.1567)	(0.1760)
AE(t)	0.2195	0.1601
	(0.1639)	(0.1508)
AE(t) Squared	-0.0442	-0.0432
	(0.0183)	(0.0170)
Years of Tenure(t)	0.1826	0.3375
	(0.1690)	(0.1546)
Years of Tenure(t) Squared	0.0139	0.0032
	(0.0220)	(0.0207)
Log-Weekly Hours Worked	-0.9740	-0.0818
	(0.3128)	(0.2295)
I[Union Bargained Contract]	0.0187	-0.3347
	(0.2674)	(0.2368)
I[Parental Benefits Available at j]	-0.3376	-0.3792
	(0.1112)	(0.1122)
I[Flexible Schedule Available at j]	-0.5724	-0.7875
	(0.1866)	(0.1745)
Log-Number of Employees at Employer j	-0.1164	-0.0796
	(0.0573)	(0.0524)
First Child Born by t	-0.2570	-0.5579
	(0.3390)	(0.2990)
Married by t	-0.5646	-0.5494
	(0.2916)	(0.2451)
Bachelor Degree by t	0.4812	0.3131
	(0.3423)	(0.3210)
Enrolled in Formal Education Program at t	0.0305	-0.4522

A4. Structural Parameter Estimates: Amenities O￿ered

Table 17: Estimated Flexible Schedule Parameters

fl 0

Table 20: Estimated Childcare Parameters

	${}^{cc}_{0}$	${}^{cc}_{1}$	$'^{cc}_{e}$	$'^{cc}_{p}$	$'^{cc}_{o}$	$'^{cc}_{fin}$	$'^{cc}_{tr}$	$'^{cc}_{oth}$
				Females				
Coeff.	-1.649	0.102	-0.027	0.127	-0.480	0.073	0.355	0.204
Asy.Std.Err.	(1.865)	(0.444)	(0.350)	(0.456)	(0.626)	(0.358)	(0.600)	(0.425)
LR Test p-Value	[0.422]	[1.000]	[1.000]	[1.000]	[1.000]	[0.378]	[0.676]	[0.329]
				Males				
Coeff.	0.706	-0.517	-0.270	0.424	-4.578	0.080	0.029	0.645
Asy.Std.Err.	(3.275)	(0.767)	(0.561)	(0.469)-1				