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 the first five to ten years of labor market experience (Manning & Swaffield 2009). For highly educated workers in particular, the gap increases over the life-cycle within occupation (Bertrand, Goldin & Katz 2010) and firm (Barth, Olivetti & Kerr 2017), and its evolution is only partly explained by childbirth and consequent labor supply decisions of highly educated women at the extensive (Light & Ureta 1995) and intensive margin (Cortes & Pan 2019).

Motivated by these facts, in this paper I study a recent cohort of young, highly educated and strongly labor market attached workers entering the United States labor market since year 2000, and investigate gender-based differences in other potential determinants of the gender wage gap. Specifically, I study whether male and female workers differ in terms of: (i) job search frictions; (ii) preferences for job specific attributes, including schedule flexibility, long hours, provision of parental leave, provision of childcare; (iii) characteristics of the job offers that workers receive, including wage and the pay penalty/premium attached to the provision of amenities.

Throughout the paper, I argue and document that these three dimensions are likely to be especially relevant in explaining wage levels and paths among young workers, and their difference across gender, even once other factors have been taken into account, including on the job human capital accumulation, labor market attachment, occupation and industry.

Consider first the relation between search frictions and wages. Both employed and unemployed young workers search for better and better jobs in order to improve their career prospects (Topel & Ward 1992). To the extent that the search process is not frictionless and takes time (Burdett & Mortensen 1998), women may be less likely to receive high-pay offers relative to men if the former search for jobs less intensively than the latter, or if some form of gender discrimination in hires exists. In both cases, the consequent low rate of arrival of job offers to women decreases their capability to improve their wage prospects by switching job and climbing the job ladder, thus making their wages lower relative to men on average.

Second, consider non wage job attributes. The perspective of a wage increase is not the unique driver of voluntary job changes among young workers, as the latter obtain utility from both wage and non wage amenities, and tend to switch jobs to increase their utility as a whole (Hwang, Mortensen & Reed 1998, Khandker 1988), rather than their wages solely. The job attributes I consider may affect workers' preferences and utility differently according to their gender. Even (and perhaps mostly) highly educated and labor market attached women may prefer amenities such as flexibility or parental leave more strongly than men, and be willing to accept wage cuts in exchange for their provision, especially if they consider those benefits as a form of employment insurance in the (possibly future) event of a childbirth[2]. For similar reasons,

[1]See Blau & Kahn (2017) for the most comprehensive review

[2]This may be true especially when parental leave is concerned, given the lack of a unified federal-level legislation on the matter in the United States. Specifically, while the Family and Medical Leave Act of 1993 mandates 12 weeks of annual maternal leave for mothers on newly born or adopted children who work in firms with more than 50 employees, unpaid parental leave is unregulated at the federal level for smallers firms. In addition, no federal-level scheme exists mandating paid parental leave. For an assessment of the most recent litarature and cross-country evidence on parental leaves, see

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 parental leave, as she knows she might otherwise jeopardize her job in the future, in the event of a childbirth. This fact limits the outside options that such woman has relative to a comparable man, in fact enabling employers to offer the woman a lower wage relative to he wage they would have offered to a man for the same job. In other words, women labor supply rigidity gives rise to monopsonistic gender discrimination.

In this paper I assess the likely existence and magnitude of gender differences in search, preferences, and job offers received in two ways. In the first part of the paper I perform descriptive analyses, and provide a variety of evidence suggesting that underlying differences in gender-specific search frictions, preferences for amenities, and job offers, may help rationalizing the diverging patterns of wages between highly educated men and women that I observe in the data. In the second part, I rely on the structural estimation of an hedonic model of job search with amenities, in order to quantify gender-based differences in the three factors mentioned above. I then use the estimated parameters of the model to characterize the average utility that workers of different genders are predicted to obtain from jobs, and to quantify the utility contribution of wages and amenities offered to workers.

Since the analysis requires to track workers careers closely, I use data from the United States National Longitudinal Survey of Youth 1997 (NLSY97), a nationally representative panel on the cohort born between 1980 and 1984, and observed yearly since 1997. The survey records comprehensive information on the characteristics of workers and of their jobs. In addition, the availability of unique employer identifiers and of weekly array data on job held and employment status allows me to cleanly construct workers' career dynamics since labor market entry, and their movements across jobs. I isolate non African-American and non Hispanic workers graduating from college by age 25 (high education), who are strongly labor market attached and enter the labor market from year 2000 as full time workers. I study these workers for the first five to ten years of their career.

The descriptive analyses are organized around the three main points of interest of the paper. I first focus on search frictions, and show that: (i) while noticeable gender differences in labor market attachment arise after the fifth year on the labor market, a difference in hourly pay arises between young men and women since the second year of labor market experience, and increases over time; (ii) gender specific returns from job changes explain slightly more than 50% of the overall gender wage gap in early careers; (iii) voluntary job changes are associated with economically and statistically significant wage gains for men but not for women, while constrained job changes due to family and mobility constraints are associated with significant

Olivetti & Petrongolo (2017).

wage losses for women but not for men.

The relation between this body of evidence and the possible existence of gender-specific search frictions is intuitive. In a Burdett & Mortensen (1998) and Hwang, Mortensen & Reed (1998) set-up, categories of workers having fewer chances of receiving job offers when employed and unemployed tend to accept lower wages and cannot attain top-pay jobs. When employed, they tend to be in jobs offering lower wages and lower utility.

Second, grounding on my previous findings, I analyze preferences for amenities. Given search frictions, even returns from voluntary job changes can be lower for women if they are more likely than men to willingly change job in order to obtain certain contractual benefits (or job attributes, or amenities) rather than a wage increase. In order to grasp whether women value job characteristics more strongly than men, I follow Gronberg & Reed (1994) and Dale-Olsen (2006), and study gender-specific job quit rates. Intuitively, if women prefer amenities more strongly than men, they will be less likely to quit their current job when amenities are provided, potentially forgoing wage rises from shopping among further job offers. I show that the average probability to quit a job decreases more strongly, when flexible schedule and parental leave are provided, for women than for men.

Third, I use the estimation of quit probabilities to understand whether male and female workers may receive different job offers. The estimation results show that the average quit rate is more negatively elastic with respect to wages for women than for men. This evidence is consistent with the fact that men draw offers from a *better* job offer distribution (Light & Ureta 1992), that is, from a distribution entailing higher wages, given amenities[3].

In the second part of the paper, I build on the Bonhomme & Jolivet (2009) model, a partial equilibrium version of the Hwang, Mortensen & Reed (1998) hedonic model of job search, to quantify the extent to which men and women differ along the three dimensions mentioned above. In the model, workers' utility depends on wages and on the amenities (flexibility, long hours, parental leave and childcare) provided at current job. Unemployed and employed workers search for jobs and face exogenous job offer arrival and job destruction probabilities. Job offers are gender specific, and depend on wages and amenities. Within gender, they are heterogeneous based on workers' ability and on their careers, proxied by aggregate occupation and industry classes. Following Bonhomme & Jolivet (2009), I estimate the distribution of employed workers across jobs and the probability to move across jobs and employment statuses implied by the model steady state through sequential Maximum Likelihood[4].

The results of the structural estimation are not always in line with priors based on the descriptive evidence explained above. First, the estimated search friction parameters do not differ across genders for employed workers. When out of work, instead, young women receive job offers less frequently than men, as each month the former have a 19% probability of receiving a job offer, while the figure amounts to 23% for men. The evidence that out of work women face stronger job search frictions relative to men is of particular interest, as workers included in the structural estimation sample are highly homogeneous in terms of labor market attachment. This

[3]Some authors have in fact relied on estimation of quit rates to provide evidence of gender-based monopsonistic discrimination using matched employer-employee data (Barth & Dale-Olsen 2009).

[4]To avoid time aggregation biases in the estimation of search frictions, I estimate the structural model on a monthly dataset covering the first 5 years of workers' experience, that I construct using the weekly arrays of the NLSY97.

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 in preferences between groups facing potentially different job offer distributions. Allowing for gender-specific preferences for amenities in a search model is also necessary to estimate gender specific search frictions. Ignoring the contribution of non-wage amenities to workers' utility would lead to an overestimation of the share of *constrained* job moves (Bonhomme & Jolivet 2009) and of the utility losses due to movements from higher to lower paying jobs. Such bias would be stronger for workers attaching higher utility to amenities.

The paper is structured as follows. In Section 2 I describe the NLSY97 data, sample selection and the main characteristics of the workers I study. In Section 3 I illustrate the descriptive analyses that motivate this work. Section 4 explains the empirical hedonic search model. In Section 5 I show the estimation results, and use the estimated structural parameters of the model to decompose workers' utility from employment relationships. Section 6 concludes.

[5]The evidence I find in this sense, however, must be considered suggestive at best. As Bonhomme & Jolivet (2009) notice as well, due to the lack of a large, employer-employee dataset, the structural model I estimate can only allow for a reduced form representation of labor demand, thus making it impossible to study firms' wage setting practices.

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.

The final sample used in the analysis includes a subgroup of non African-American and non Hispanic, sufficiently labor market attached high-education workers whose careers are followed from the year they enter the labor market to, at most, 10 years later. For each individual, I make use of background information, demographics, education and labor market information. Job-specific information is collected for the job each worker declares to be employed at in the weekly arrays of the NLSY. Since weekly employment-status information is collected for all weeks of all years from 1999 to 2016, job-specific information is observable for years when the NLSY survey was not administered as well, using employer-specific identifiers.

For every individual, I define the year of labor market entry as the first year such that, for two consecutive years, a worker is employed for more than 26 weeks (Loprest 1992) per year and for at least 35 hours per week (Blau & Kahn 2017) in the job where the lowest amount of weekly hours worked in a given year is reported[6].

Once the first year in the sample is defined, I retain information regarding the first ten years in the labor market at most. Hence, I drop information for labor market years 11-on whenever available. In addition, I require each worker to be followed for at least five years. Consecutively, I drop all individuals who entered the labor market from 2013 on. I further restrict the sample to highly labor market attached individuals, defined as workers who never exit the labor market and are never unemployed for as many as (or more than) 52 consecutive weeks by the fifth year of labor market experience.

I make use of the weekly arrays of the NLSY97, where the employment status and the employer identifier of each employed worker are provided for every week from 1999 to 2016, in order to construct yearly tenure, weeks worked, job duration, job changes, between jobs gaps out of work and gap duration (if any).

After workers are characterized, I define missing all data corresponding to cells for which wage information is missing. In an effort to retain a reasonable number of observations per year, I define *relevant jobs* as either the first or the last job held by a worker in a year (in chronological order), or any job in between lasting more than 13 weeks. If a worker has missing information for any *irrelevant job*, that is for any job lasting less than 13 weeks and not corresponding to the first job held in a year, I retain the worker in the sample and drop from the sample any information related to the irrelevant job.

Since I am interested in analyzing the relations between mobility, wage gains, employer characteristics and job amenities, I drop individuals who are self-employed workers in at least one year. Finally, I drop individuals who report at least once unreasonably high hourly wages

[6] Because of this definition, the first year of employment may occur before the last year spent by a worker in formal education.

(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 five years and until the first missing non-imputable missing wage when employed is observed. As soon as a non-imputable missing wage is observed in an employment spell, the following work history of the worker is ignored. All workers are observed for ten years at most.

Table 1 reports the average characteristics of the male and female samples for all relevant individual, job and employer specific time invariant and time varying variables, and results of t-tests for differences in means. For time varying characteristics, means and t-tests refer to the first and last year in the sample. The table shows that differences exist between male and female workers both in time constant characteristics and time varying characteristics.

Regarding education, while all workers in the sample obtain their college degree by age 25 by construction, women are approximately 9% more likely than men to have obtained their college degree by the time of labor market entry (Panel (b)) and about 55% more likely than male workers to obtain a master degree by age 26 (Panel (a)).

Family formation decisions look similar between men and women. Almost 70% of workers of both sexes marry by 2015 and, while women (51%) are significantly more likely to have a child than men (45%) by the last year in the sample, only 6% of them are mothers at labor market entry. Both male and female workers who have a child are about 28 years old on average at first childbirth. It happens 4 to 5 years after they enter the labor market. The timing of childbirth is important to notice. As a matter of fact, it is after the fifth year since labor market entry that significant differences in labor market attachment arise between male and female workers in my sample. As I will show in Section 3, by the time such differences become evident, a gender gap

[7]Looking at the full sample of NLSY97 individuals who obtain at least a bachelor degree by Round 17, a 42% share are males while approximately 58% are females.

[8]The construction of the sample of interest is detailed in Appendix Section A1.

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
Employer j provides flexible schedule	0.536	0.447	0.089**	0.037	737
Employer j number of employees	833.766	346.459	487.308**	234.249	748
Average weekly hours worked at j	44.189	40.755	3.434***	0.802	752
Hourly rate of pay at j (in 2005 Dollars)	27.437	23.437	3.999***	1.147	752
Total number of weeks employed in t	41.579	37.325	4.254***	1.164	752
Duration in years of employment spell	5.534	5.410	0.123	0.213	752
Duration in weeks of employment spell	285.442	270.163	15.279	10.921	752

Regarding job and employer specific characteristics, women are more likely to work for employers offering some form of parental leave, but they are never more likely than men to be offered schedule flexibility. Importantly, the share of individuals working for employers offering non-wage benefits rises over time for both men and women. As workers change more than one 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 $16 hourly salary), and they work as many hours per week and as many weeks per year (Panel (b)). By the last year in the sample, however, women's average weekly hours of work decrease while men's work hours rise. Women work three weeks less than men during their last year in the sample and earn on average 4$ less per hour worked (Panel (c)). The difference between the hours worked by men and women by the last year in the sample is relevant and may contribute to explain why, by the same time, men are more likely to work for employers providing flexible schedule.

Interestingly, women end up working for employers whose dimension, measured by the number of employees in the interview year, is significantly smaller than the dimension of employers where men work, in spite of a similarity in employer dimension at the beginning of their careers. Given the positive relation between employers' dimension, wage offers and employees' utility predicted by job search models *à la* Hwang, Mortensen & Reed (1998), the evidence above suggests that female workers may both be subject to stronger search frictions relative to men, entrenching their ability to select into better jobs over time, and be more likely to experience constrained job changes.

Tables 2 to 4 describe workers' mobility during their early careers. Male and female workers look similar in terms of both labor market and work attachment during the first five years on the labor market. This fact is driven, at least to some extent, by sample selection, and most differences emerge after the fifth year in the labor market.

Table 2: Frequencies of Employment Statuses

	Males	Females	Diff.	Std. Error	Obs.
	(a) First Five Years on the Labor Market				
Job-to-Job transition	0.415	0.364	0.051*	0.028	1281
Gap in weeks between two consecutive jobs	5.230	5.258	-0.028	0.599	1159
Gap in weeks between jobs conditional on Gap > 0	9.809	8.725	1.084	0.952	665
Employed	0.795	0.784	0.011	0.011	6073
Unemployed	0.063	0.062	0.002	0.006	6073
Out of Labor Force	0.131	0.144	-0.014	0.009	6073
Employed but not working	0.000	0.001	-0.001	0.000	6073
Other, not working	0.011	0.010	0.001	0.003	6073
	(b) After Fifth Year on the Labor Market				
Job-to-Job transition	0.412	0.374	0.039	0.043	567
Gap in weeks between two consecutive jobs	8.592	8.733	-0.141	1.565	567
Gap in weeks between jobs conditional on Gap > 0	14.621	13.942	0.679	2.392	347
Employed	0.653	0.606	0.047***	0.014	4998
Unemployed	0.036	0.029	0.007	0.005	4998
Out of Labor Force	0.069	0.125	-0.057***	0.008	4998
Employed but not working	0.000	0.000	0.000	0.000	4998
Other, not working	0.243	0.240	0.003	0.012	4998

Table 2 characterizes employment status spells[9]. An employment status spell is defined as a set of consecutive weeks in a given year when a worker is observed in a certain employment status. Whenever employed, direct job-to-job transitions can be identified by observing week-by-week changes in the unique identifier of the employer where a worker is employed.

The table shows that, out of all the observed spells, male and female workers are observed a similar fraction of times in each employment status by the fifth year on the labor market. After year of experience 5, women are significantly less likely than men to be observed in an employment spell (61% of the time versus 65% of the time) and are twice more likely than men to experience out of the labor force spells.

Regarding transitions, all workers experience out of labor gaps of similar duration when changing employer. However, male workers are overall 5 percentage points more likely than female workers to experience job-to job transitions. This fact is relevant, to the extent that it may suggest that on the job search may be less costly and more successful for men than for women. Related to this, it is interesting to notice that, while the number of job changes and job losses decreases over time in absolute terms, the share of workers experiencing job to job transitions is virtually the same by the fifth year of experience later on. 41% of employment status changes for male workers consist of job-to-job transitions during both the initial and the final sample periods, while 36% is the figure for female workers.

For both male and female workers, labor market attachment decreases after the fifth year in the labor market. Table 3 shows that both men and women spend less than two spells and approximately 11 weeks overall out of the labor market at the very beginning of their career, while they spend approximately 46 (men) and 59 (women) weeks out of labor later on.

Table 3: Number of Career Interruptions and Total Number of Weeks Out of Employment

	Males	Females	Diff.	Std. Error	Obs.
	(a) First Five Years on the Labor Market				
Total number of spells out of employment	1.622	1.774	-0.152	0.166	752
Total number of weeks out of employment	11.530	12.953	-1.422	1.386	752
	(b) After Fifth Year on the Labor Market				
Total number of spells out of employment	2.381	2.821	-0.440***	0.164	752
Total number of weeks out of employment	45.567	58.917	-13.350***	4.328	752

Similar differences can also be observed in Table 4, where I report the average number of weeks spent by workers in four categories of employment status in a year.

[9]The share of job to job transitions is calculated as the number week-to-week employer changes, over the number of times workers enter a new employment relationship in a certain week. The total number of transitions into an employment relationship includes 122 transitions into employment of workers who are observed out of the labor force or into unemployment at the beginning of the first year on the labor market, and who find a job over the course of that year. These transitions cause the discrepancy between the number of non missing observations in the first and second line of Panel (a).

Table 4: Yearly Continuous Weeks in Employment Status

	Males	Females	Diff.	Std. Error	Obs.
	(a) First Five Years on the Labor Market				
Employed	39.466	38.454	1.013**	0.501	4789
Unemployed	6.756	7.346	-0.590	0.759	378
Not in Labor Force	6.909	6.235	0.673	0.539	841
Other, not working	11.448	22.824	-11.375***	3.251	63
	(b) After Fifth Year on the Labor Market				
Employed	42.365	39.254	3.111***	0.592	3129
Unemployed	9.842	11.554	-1.712	1.847	159
Not in Labor Force	8.493	16.025	-7.532***	1.283	505
Other, not working	23.969	25.196	-1.227	0.891	1205

Overall, women spend more weeks per year out of employment and fewer weeks per year in employment. Yet, the gap in the average number of weeks employed rises from less than one to almost three weeks between the first five years on the labor market and the consecutive years.

Three main facts emerge regarding workers' characteristics. First, male and female workers' job specific characteristics, labor market attachment and labor market outcomes evolve over time. Second, male and female workers in my sample are remarkably similar in terms of labor market attachment for at least as much as half the time I observe them (five years) and for the entire time-span I use in the structural estimation of job search and preferences parameters. It reduces concerns regarding whether results from further analyses are driven by differences in willingness to invest in own careers. Third, since labor market attachment differences between male and female workers do emerge over time, such differences need to be taken into account.

In the next section I analyze the early career wage gap between the highly educated male and female workers in the *NLSY97* sample. I document that job change determinants (e.g. preferences, likelihood of receiving job offers and potentially labor-demand driven in the job offers that workers receive) and consequent outcomes, help rationalizing its emergence and its increase over time in the labor market, even when labor market attachment is duly accounted for and even when otherwise remarkably similar male and female workers are compared.

3 Descriptive Analyses

3.1 Wage Profiles and Gains from Experience and Job Change

The objective of this section is to provide evidence that search and job change dynamics play a non-negligible role in the emergence and expansion of the gender wage gap, even for high-education and highly labor market attached workers. The paths of log-wages in Figure 1 show that a gender difference in log-wages arises among both young highly educated workers, and workers without a college degree, soon after labor market entry.

The two graphs in Figure 1 report the composition adjusted mean log-wages of male and female workers entering the labor market by 2007, by years of experience, the latter being defined as years since labor market entry.

The sample in panel (a) includes workers who obtain their bachelor degree by age 25 (*high* *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 $y_j \in \{2000, ..., 2007\}$. w_{it} is individual i log wage (in 2005 \$) in year of experience $t \in \{1, ..., 10\}$. Then the log wage in year of experience t of an individual i of gender f_i belonging to cohort y_i is

$$w_{it} = \beta_{0t} + \beta_{1t} f_i + \sum_{j=2000}^{2007} \delta_{jt} y_{ji} + \sum_{j=2000}^{2007} \eta_{jt} y_{ji} f_i + \nu_{ijt}$$

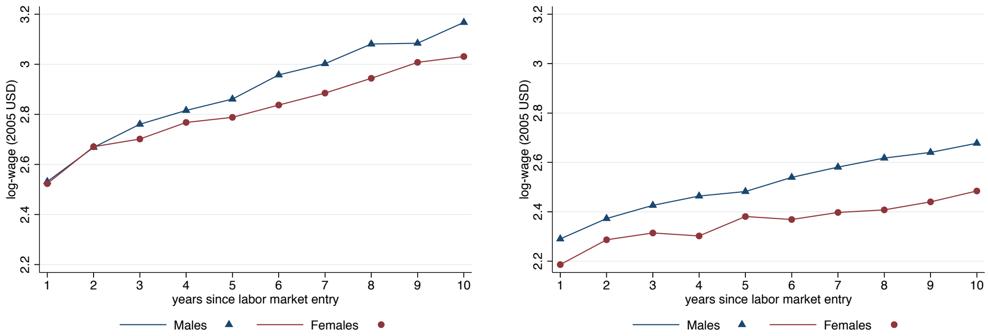
Where the subscript t indicates that a separate regression is estimated for every year of experience, so that coefficients of all variables are allowed to vary across years in the labor market.

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 the present value of their current state. It means that the wage that a worker currently receives is the maximum wage that has ever been offered to the worker since the beginning of his/her career and, as pointed out by Topel (1991), the maximum cannot decrease as workers keep sampling wage offers from the market wage offer distribution, under the assumption that the distribution is stable over time. General human capital refers to the set of skills that workers learn progressively while working and that are not specifically related to a single job or employment relation. In addition, depending on the definition of experience used, returns to experience may capture, more or less implicitly, gains from labor market and work attachment and from job continuity (Light & Ureta 1992).

As a first step, I show that returns to experience are higher for male than for female workers in early careers. In addition, and accounting for the gender differences in neatly defined work and labor market attachment observed in the previous section, I show that this difference in returns to experience is not driven by different levels of labor market attachment between male and female workers.

As a second step, I use a Blinder-Oaxaca (Blinder 1973, Oaxaca 1973, Fortin, Lemieux & Firpo 2011) decomposition to analyze the contribution of returns to experience to the wage gap, using a measure of actual experience that cleans out the effect of differences in subtly defined labor market attachment. Hence, I interpret returns to experience in the decomposition as returns to both *search* and *general human* capital. I show that most of the contribution 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. Following Light & Ureta (1995) I estimate raw returns to experience using three different measures of experience. The first measure, *potential experience* is defined as the number of years since labor market entry[11]. The second measure, *actual* (or aggregate) *experience* is defined as the neat total amount of time, in years, that an individual has spent working since labor market entry.

$$\text{exp}_{iJt} = \frac{\sum_{j=1}^{J} \text{n. weeks worked in year of exp. j}}{52}$$

Where $J = 1, ..., 10$ is the year of experience for a worker observed in calendar year t. Both potential and actual experience models include the experience measure in quadratic form. The third measure of experience, that I name *work history* as Light and Ureta (1995) do, is a set of variables, one for each year since labor market entry that capture, for each year, the share of time spent working.

The potential and actual experience models, as it is standard in the literature, can be written as

$$w_{it} = \alpha + \beta_0 \text{exp}_{it} + \beta_1 \text{exp}_{it}^2 + x_{it}'\delta + \varepsilon_{it} \tag{1}$$

Where w_{it} is the log-wage of worker i at time t, x_{it} is a vector of control variables and $\varepsilon_{it} = \nu_i + u_{it}$, ν_i is an individual-specific fixed effect and u_{it} is a mean-zero error term uncorrelated with the regressors.

Following Light and Ureta (1995), the work history model can be written as

$$w_{it} = \alpha + \sum_{\iota=1}^{I} \beta_\iota \text{exp}_{i,\iota t} + x_{it}'\delta + \varepsilon_{it}$$

Where $\text{exp}_{i,\iota t}$ = (n. weeks worked ι years ago)/(52). The variable takes value 0 if ι years before t a worker had not yet entered the labor market or if the worker experienced a one year long career interruption. Dummy variables are included in the actual experience and work history models to control for the difference between the last two cases.

[11] Since I define and observe labor market entry, the definition of potential experience I use differs and is cleaner than its more broadly used definition, where potential experience is calculated as the sum of years since one worker left education + 6.

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 separately for men and women through fixed-effect estimator[12].

The results of the estimations are reported in Table 5 and Appendix Table15. Appendix Table 15 reports the coefficient estimates from the different models. In Table 5 I report the estimated ratio between the log-wage that workers are predicted to obtain in selected years of experience at the end of the first year of tenure and the log-wage they are predicted to obtain at the beginning of the second year on the labor market. The fitted values for log-wages are computed for individuals who have worked at least 50 weeks in the previous year, who work between 41 and 50 hours per week on average and who live in a Metropolitan Statistical Area and not in the Southern region of the United States.

Table 5: Gains from Experience

	Males			Females		
	Work Hist.	Actual Exper.	Potential Exper.	Work His.	Actual Exper.	Potential Exper.
	(1)	(2)	(3)	(4)	(5)	(6)
	(a) One Year of Tenure			(a) One Year of Tenure		
Experience 2	1.063	1.050	1.000	1.075	1.040	1.000
Experience 4	1.285	1.273	1.198	1.234	1.216	1.150
Experience 6	1.554	1.517	1.414	1.383	1.402	1.314

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 experience, reside in metropolitan statistical areas and do not reside in the South, and have worked for at least 49 weeks over the previous year. Work Hist. = Work History model; Aggregate Exper. = Aggregate Experience model; Potential Exper. = Potential Experience Model. All regressions are weighted using NLSY97 panel weights.

The measures of experience listed above capture different aspects of workers' behavior on the labor market. *Potential experience* can be interpreted as a raw measure of general human capital and search capital. As the wage-ratios in Table 5 (Col. (3) and (6)) show, returns to experience appear to be higher for young, highly educated male workers relative to their female counterparts. However, part of this difference may be driven by the fact that some women appear to experience longer career interruptions when weekly career arrays are observed. The definition of potential experience does not allow to measure differences in the amount of work and labor market participation at the weekly level.

The log-wage ratios predicted by the estimation of the *actual experience* models (Col. (2) and (5)), however, show that gender differences in returns to experience persist even when men and women endowed with the same amount time spent working are compared.

The results from the estimation of *the work history* model, that accounts for actual experience in a more flexible way and captures the possibility that the timing of experience accumulation affects wages, further corroborate the result obtained when estimating the actual experience model.

Overall, the evidence in Table 5 suggests that gender differences in wage increases following

[12]The results are qualitatively unaffected when the models are estimated through OLS and when the hours-dummies are replaced by the logarithm of weekly hours.

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 can be thought of as a measure of general human capital and search capital neat of labor market attachment. The descriptive evidence above suggests that returns to actual experience are different for men and women. In the next step, I use an Oaxaca-Blinder decomposition of the log-gender wage gap in order to understand to which extent *human capital* vs. *search and job changes* matter in determining the magnitude of the raw gender wage gap observed between young high skill men and women in early careers.

I estimate the actual experience model (1) through fixed-effect estimator separately on male and female workers, controlling for years of tenure at current employer and tenure squared, whether a worker has obtained his/her bachelor degree by year t, the number of times (i.e. spells lasting at least one week) a worker exited the labor force, the size of current employer j measured by the logarithm of number of employees working at j in time t. I do not control for occupation and industry categories. Following Blau & Kahn (2017) I do not control for variables related to fertility and family formation decisions to avoid exacerbating sample-selection biases that may invalidate the decomposition.

I decompose the predicted gender wage gap between male and female workers, where the counterfactual is the wage what women workers would have obtained if their productivity related characteristics where priced according to the male workers wage structure (Fortin, Lemieiux & Di Nardo, 2011). That is, I perform the decomposition as follows. Let f_i be an indicator variable for female workers. The average wage gap can be decomposed as

$$\hat{E}[w_{it}|f_i = 0] - \hat{E}[w_{it}|f_i = 1] = \sum_{k=1}^{K} \bar{x}_{kf} \left(\hat{\beta}_m - \hat{\beta}_f\right) + \sum_{k=1}^{K} \hat{\beta}_{mk} \left(\bar{x}_{km} - \bar{x}_{kf}\right) \tag{2}$$

The left hand side of equation (2) is the difference in the estimated average log-wage between men and women. The first component on the right-hand side represents the *wage structure* component of the gender wage gap. It reflects the portion of the average gender wage gap due to gender differences in the remuneration of the same productivity related characteristics. It also includes the *unexplained* portion of the gap (i.e. the component explained by different *constant* terms in the wage regressions)[13]. The second part represents the *characteristics* component of the wage gap. It reflects the portion of the average pay gap due to differences in average observable characteristics between men and women.

Table 6, panel (a) reports the results of the baseline decomposition. First, it should be noticed that, of the 9.6 log-points wage gap estimated in the first ten years of labor market experience, 97% can be ascribed to the *wage structure* component of the gap. This result is not particularly surprising, considering the highly selected individuals composing the sample under study. Second, while differences in formal education (captured by the college graduation dummy

[13]The unexplained gap cannot be identified in panel data using fixed effect estimator. I report its estimated value in Table 6 for completeness.

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

	Total Gap	Wage Structure	Characteristics
	(a) Not Controlling for Number of Job Changes		
Total	0.096	0.092	0.004
Actual Experience	0.047	0.037	0.009
Tenure	0.056	0.057	-0.001
Firm Size	-0.024	-0.024	-0.000
Education	-0.157	-0.157	0.000
Career Interruptions	0.012	0.016	-0.004
Unexplained Gap	0.163		
	(b) Controlling for Number of Job Changes		
Total	0.096	0.089	0.008
Job Changes	0.052	0.053	-0.001
Actual Experience	-0.033	-0.037	0.004
Tenure	0.097	0.093	0.004
Firm Size	-0.020	-0.020	-0.000
Education	-0.150	-0.150	0.000
Career Interruptions	-0.005	-0.005	0.000
Unexplained Gap	0.154		

As we can see from Table 6, panel (b), once job changes are controlled for, the contribution of *actual experience* to the gender wage gap becomes negative, while 53% of the wage gap is explained by job changes. Interestingly, the entire job-change component of the gender wage gap is explained by gender differences in the returns to job changes.

This finding is consistent with the descriptive analyses reported in the previous section. Importantly, it supports the idea that, when observationally similar workers are compared, search matters in explaining residual differences in labor market outcomes between male and female workers. The fact that gender-specific job change premia absorb the entire portion of the gender wage gap previously attributed to experience can be rationalized by a Burdett & Mortensen (1998) type model where female workers are less likely to receive job offers relative to men and therefore face a distribution of wage offers that is first order stochastically dominated by the distribution of wages offered to male workers. At the same time, differences in preferences over non-wage job characteristics may also explain the results above, since women may be *willing* to forgo some wage gains from job changes in exchange for the provision of certain amenities.

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

3.2.3 Gender Differences in Gains from Job Changes: Differences 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 differences 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 differ between men and women once different returns to job changes have been accounted for. Hence I estimate a model of the form

$$\begin{aligned} w_{it} = \alpha + \beta_1 \text{exp}_{i,t-1} + \beta_2 \text{exp}^2_{1,t-1} + \delta \text{change\_job}_{i,t-1} + \\ + \gamma \text{change\_job}_{i,t-1} * \text{exp}_{i,t-1} + \eta \text{change\_job}_{i,t-1} * \text{exp}^2_{i,t-1} + x'_{i,t-2}\psi + \varepsilon_{i,t} \end{aligned} \quad (3)$$

Where change_job is an indicator variable taking value 1 for workers who changed job between $t-2$ and $t-1$. $\varepsilon_{it} = \nu_i + u_{it}$ where ν_i is an individual specific fixed effect and u_{it} is an error term orthogonal to the regressors.

The parameter of interest, γ, indicates the difference 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 differ 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 offer 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 offer 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 $\hat{\gamma}$ and differences in it between male and female workers are of interest, the OLS estimated coefficient cannot be given a *causal* interpretation due to unobserved differences 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 effect 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 $\hat{\gamma}$ would represent a lower bound to the actual returns to job change.

On the other hand, the possibility that workers in certain *career* jobs or who are more *career oriented* have more opportunities to search for and switch jobs at the beginning of their career. The counterfactual wage paths of these workers had they not changed job, however, are likely to be steeper than the wage path of workers who do not change job. In this case, the estimated $\hat{\gamma}$ would overestimate the actual returns to job change.

In order to account for potential different trends in the evolution of log wages between workers who change jobs and workers who do not, I first estimate equation (3) without any control, then estimate it including a number of variables controlling for pre-existing (i.e. at $(t-2)$) worker, job and employer characteristics. In addition, I re-estimate equation (3) by re-defining the control group. Instead of comparing the time t wage of workers who changed job at $t-1$ with the time t wage of *all* workers who did not change job, I control for whether a worker who did not change job at $t-1$ did so at t, and include interaction of this variable with $t-1$ experience and its square, conditional on individual, job, and employer characteristics.

The underlying idea is that workers who change job only one year later than workers who switch job at $t-1$ are more similar, in terms of counterfactual wage path, than the set of all workers who did not change job at $t-1$.

Since job change happens between $t-2$ and $t-1$, controls for pre-existing characteristics are evaluated at $t-2$. Control variables are used here in an attempt to compare time $t-1$ job changers whose career path in the previous job was as similar as possible to time $t-1$ job stayers, conditional on $t-1$ actual experience. Control variables include two dummy variables indicating whether a worker was enrolled in school or college at $t-2$, whether the worker obtained his/her Bachelor degree by $t-2$, the $t-2$ logarithm of weekly hours worked, years of tenure and its square, employer dimension measured as the log of number of employees, availability of parental benefits and flexible schedule, union status and total number of spells out of the labor force.

As job-change decisions may be driven or affected by macroeconomic conditions as well, the model includes the average annual unemployment rate measured in the US region where the worker lived at $t-2$. Information about annual unemployment rate by US region is collected through the Bureau of Labor Statistics series from 2000 to 2016.

The control variables capture the idea that job-change decisions can be more or less strongly motivated by workers' human capital characteristics, by their labor market attachment and by the working conditions a worker faced at his previous job. Controlling for these characteristics helps isolating mobility decisions that are motivated by the arrival to job offers of different value to workers with similar backgrounds.

The estimation results are reported in Table 7.

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 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 first two panels on the left report the estimates of the baseline model with and without controls; the last two panels add a dummy variable indicating job change at time t only and its interactions with the actual experience polynomial. Robust standard errors adjusted for serial correlation are reported in parentheses. The main variable of interest is the interaction term between time $t-1$ experience and $t-1$ job change. In all specifications its estimated coefficient is positive, but it is two to six times as large for males than for females, and it is never statistically significant.

Consider male workers first. Observing the models with control variables only, the estimated coefficient for male workers implies that the time t log-wage of a worker who changed job at $t-1$ is approximately 10 log-points higher than the wage of a workers with the same $t-1$ experience and with the same tenure at $t-2$. The fact that controlling for tenure at $t-2$, among other things, contributes to increase the coefficient of the job-change interaction is not surprising. As far as wages tend to rise with seniority and that, conditional on experience, the probability of changing job decreases with tenure, the estimator of returns to job-change in the model without controls is likely to be downward biased. Regarding women, the impact of job changes on wages is never higher than 3 log-points and it is never statistically different from zero.

The evidence in Table 7 suggests that job changes can play a role in the rise and expansion of the gender pay gap within the first ten years in the labor market, even among a subgroup of highly educated nd work attached individuals.

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

$$\begin{aligned} w_{it} = \alpha + \beta_1 \text{exp}_{i,t-1} + \beta_2 \text{exp}^2_{1,t-1} + \sum_{k=1}^{K} \delta_k \text{change\_job\_reason}_{k,i,t-1} + \\ + \sum_{k=1}^{K} \gamma_k \text{change\_job\_reason}_{k,i,t-1} * \text{exp}_{i,t-1} + \\ + \sum_{k=1}^{K} \eta_k \text{change\_job\_reason}_{k,i,t-1} * \text{exp}^2_{i,t-1} + x'_{i,t-2}\psi + \varepsilon_{i,t} \end{aligned} \tag{4}$$

The reasons for leaving $(t-2)$ job are: *job destruction* (layoff, plant closure, worker was fired, end of a project), *shopping* (the worker left to look for or accept another job); *family constraints* (including pregnancy); *work environment* (worker unsatisfied with pay, working conditions, relationships with colleagues and/or supervisor); *mobility constraints* (personal mobility constraints or lack of appropriate transportation infrastructures); *other* (legal or medical problems, school enrollment and other unknown reasons). The other components of the model are defined as in the previous specification.

The result of the fixed effect estimation of the model are reported in Table 9, using different specifications that progressively include time dummies, time linear trends, and time trends 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 $\hat{\gamma}_k$ 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*. γ_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 be partly inferred by quit rates Gronberg & Reed (1994)). In order to explore whether it is plausible to imagine that male and female workers may be different in terms of preferences for amenities, as a next step I study their mobility decisions by estimating models of job quit.

A workers is defined as a job quitter if his or her first employer in year $(t + 1)$ is different from his or her first employer in year t. According to random search models à la Burdett & Mortensen (1998), quit rates should decrease as the earned wages increase. The higher the current wage, the lower the probability of receiving a job offer whose wage value is higher, the lower the probability of quitting the current job. Once hedonic elements are included in the model as in Hwang, Mortensen & Reed (1998), however, the worker evaluates jobs by comparing utility flows rather than wages solely. Hence, an improvement in job characteristics that accrue positively to a worker's utility must decrease the probability that a worker quits a certain job.

Supposing that young female workers attach more weight to job amenities such as flexibility or the availability of some form of of parental leave than their male counterparts, we should observe the quit rate of female workers to fall more rapidly when those amenities are provided compared to when they are not.

I estimate the probability of job quit separately for male and female workers. In order to mitigate concerns about omitted variable bias due to the fact that quit rates may vary systematically with individual-specific unobserved productivity correlated to workers' observable characteristics, I estimate the quit probabilities through conditional (or fixed effect) logit model (Chamberlain 1980, Kitazawa 2012). The models take the following form:

$$\begin{aligned} y^*_{ijt} &= z'_{ijt}\xi + \nu_i + u_{ijt} \\ &= \alpha + \beta w_{it} + \gamma \mathbf{I}\left[\text{Parental Benefits}_{ijt}\right] + \delta \mathbf{I}\left[\text{Flexible Schedule}_{ijt}\right] + x'_{ijt}\eta + \nu_i + u_{ijt} \qquad (5) \end{aligned}$$

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

$$\Pr\left[y_{ijt} = 1 | z_{ijt}, \nu_i\right] = \frac{\exp\{z'_{ijt}\xi + \nu_i\}}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \tag{7}$$

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, $\mathbf{I}\left[\text{Parental Leave}_{ijt}\right]$ takes value 1 if employer j offers paid leave, unpaid leave or child care to i in t, $\mathbf{I}\left[\text{Flexible Schedule}_{ijt}\right]$ 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 with observable characteristics and with quit behavior in a non-linear probability function, by exploiting the within-individual and over time variation in the binary quit outcome and in regressors, and relying on the properties of the Logit functional form of the quit probability to cancel out ν_i and identify the partial effects of the regressors on the log-odds of job change (Chamberlain 1980, Wooldridge 2002). While the incidental variable problem does not allow to identify the partial effect of time-varying characteristics on the probability of job change, a recent contribution by Kitazawa (2012) shows that the average elasticity and semi-elasticity of the probability of job change with respect to time varying regressors can be consistently estimated within the conditional logit framework[15].

Since within-individual changes over time in the outcome variable as well as in the regressors are necessary for identification, the model can only be estimated for the subsample of individuals who change at least one job within 5 to 10 years in the labor market.

The results of the estimated conditional logit models for male and female workers are reported in Table 10 and Appendix Table 16. Specifically, Appendix Table 16 reports the estimated vector of coefficients ξ, representing the partial effects of individual, employer and labor market specific characteristics on the log-odds ratio of job change. Table 10 reports Kitazawa (2012) elasticities (or semi-elasticities, depending on the definition of each regressor).

Overall, Table 10 provides evidence that, on average, the probability of leaving a job decreases faster for female workers than for male workers following changes in both wages and non wages

[14] Sector-specific or different local labor demands generate cross-workers heterogeneity in the distribution of wages available to different categories of workers, and potentially different mean wages available to different workers. The quit rates decrease with in the unobserved mean of the wage offer distribution (Mortensen 1986) and in own wage. Own wage is positively correlated with mean wage. Hence, disregarding any source of labor demand heterogeneity may lead to estimate a too strong, biased and inconsistent reaction of the probability of job change with respect to own wage.

[15] A summary of Kitazawa (2012) theoretical argument is reported in Appendix Section A2.

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
$\mathbf{I}[\text{Job}(t+1) \neq \text{Job}]$		
Log-Hourly Wage in 2005 USD	-0.4120***	-0.6739***
	(0.1337)	(0.1492)
$\mathbf{I}$[Parental Benefits Available at j]	-0.2879***	-0.3213***
	(0.0948)	(0.0951)
$\mathbf{I}$[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 male and female workers. Within each labor market, a continuous mass of workers face a continuous mass of firms. When employed, workers obtain utility from (log) wage (w) and a vector of amenities ($\mathbf{a} = [a_1, ..., a_K]$). The amenities of interest are: parental leave (either paid or unpaid), employer provided or sponsored child care, flexible schedules and long hours. Workers utility function is $u(w, \mathbf{a}) = w + \delta'\mathbf{a}$ and it does not depend on workers' ability or career. For each $a_k \in \{a_1, ..., a_K\}$, δ_k represents the workers' marginal utility of a_k and it corresponds to their marginal willingness to pay out of wage in order to be offered amenity a_k.

A job consists of a bundle $(w, \mathbf{a})$ and the offer of jobs follows a cumulative distribution $F^g(.|\text{car}_{occ}, \text{car}_{ind}, b)$, $g \in \{f, m\}$, which is unobserved and taken as given. As in the Bonhomme & Jolivet (2009) model, this assumption implies that labor demand is not modeled in this framework, so that the model is in partial equilibrium. The g superscript, that I drop from now on for simplicity, formalizes the labor market gender segregation that I assume. As mentioned above, within genders, F varies depending on workers' career, defined by occupation (car_{occ}) and industry (car_{ind}), and ability (b).

Both employed and unemployed workers look for jobs. Transitions across employment statuses are defined following Bonhomme & Jolivet (2009). An employed worker obtains an outside offer at rate λ_1 while the arrival rate of offers for unemployed workers is λ_0. Jobs can be destroyed. In this event, workers either lose their job at rate q, or contemporaneously obtain an outside job offer (rate λ_2). The λ_2 parameter that Bonhomme & Jolivet (2009) add to the basic Hwang, Mortensen & Reed (1998)) set-up is of particular interest here. On the one hand, it allows to quantify potential gender differences in the relative likelihood of *constrained* and *unconstrained* job moves. On the other hand, it can highlight gender differences in the ability of workers who received a job termination notice to elicit job offers that would avoid entering unemployment.

The steady state of the model is characterized by a mobility rule for employed workers and by a joint distribution of $(w, \mathbf{a})$ across employed workers. The mobility rule takes the following form

$$P(\text{leave}|w, \mathbf{a}, \text{car}_{occ}, \text{car}_{ind}, b) = q + \lambda_2 + \lambda_1 \bar{F}_u(w + \delta'\mathbf{a}|\text{car}_{occ}, \text{car}_{ind}, b) \tag{8}$$

The monthly probability that employed workers leave their jobs is the sum of the job destruction (q) probability, the constrained job-to-job transition (λ_2) probability and the probability that they receive a job offer yielding an utility level strictly higher than current job ($\lambda_1 \bar{F}_u(w + \delta'\mathbf{a}|\text{car}_{occ}, \text{car}_{ind}, b)$).

The steady state distribution of jobs across employed workers is found observing that at steady state the flows of workers in and out of unemployment must be the same, so that

$$\lambda_0 U = q(1 - U) \tag{9}$$

Implying that the steady state share of unemployed workers is $U = q/(\lambda_0 + q)$ and the steady state share of employed workers is $(1 - U) = \lambda_0/(\lambda_0 + q)$.

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 $G(.|\text{car}_{occ}, \text{car}_{ind}, b)$ the distribution of jobs across employed workers and $G_u(.|\text{car}_{occ}, \text{car}_{ind}, b)$ the observed distribution of utility levels, at steady state

$$\lambda_0 U F_u(u|.) + \lambda_2 F_u(u|.)(1-U)\bar{G}_u(u|.) = q(1-U)G_u(u|.) + \lambda_2 \bar{F}_u(u|.)(1-U)G_u(u|.) + \\ + \lambda_1 \bar{F}_u(u|.)(1-U)G_u(u|.) \quad (10)$$

It implies

$$G_u(u|.) = \frac{F_u(w + \delta'\mathbf{a}|.)}{1 + k\bar{F}(w + \delta'\mathbf{a}|.)} \quad (11)$$

where $k = \lambda_1/(q + \lambda_2)$, and

$$\frac{g(w, \mathbf{a}|.)}{g_u(w + \delta'\mathbf{a}|.)} = \frac{f(w, \mathbf{a}|.)}{f_u(w + \delta'\mathbf{a}|.)} \quad (12)$$

As Bonhomme & Jolivet (2009) show, the above results imply that it is possible to map the observed cross section of $(w, \mathbf{a})$, G to the unobserved job offer distribution F as

$$g(w, \mathbf{a}|.) = (1 + k)\frac{f(w, \mathbf{a}|.)}{[1 + k\bar{F}(w + \delta'\mathbf{a}|.)]^2} \quad (13)$$

Where $k = \frac{\lambda_1}{q+\lambda_2}$ is a measure of search rigidity. The higher k, the higher the rate of finding a job offer relative to the sum between the rate of a *constrained* move and the job destruction rate, the less rigid the search process. g is the observed cross sectional distribution of wages and amenities, f is the unobserved density of job offers and $\bar{F}(u|.) = 1 - F(u|.)$, is the probability of receiving a job offer providing utility higher than the utility level obtained at current job.

Estimation requires econometric assumptions on how firms determine wages and amenities offers. I show below how the estimated model is affected by ability b and careers as defined above. Specifically

$$w^*(b, \text{car}_{occ}, \text{car}_{ind}) = \mu_0^w + \mu_1^w b + \rho'\mathbf{a}^* + \sum_{occ=1}^{3} \varphi_{occ}^w \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^w \text{car}_{ind} + \sigma_w \varepsilon_w \quad (14)$$

$$a_k^*(b, \text{car}_{occ}, \text{car}_{ind}) = \mathbf{1}\{\mu_0^{a_k} + \mu_1^{a_k} b + \sum_{occ=1}^{3} \varphi_{occ}^{a_k} \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{a_k} \text{car}_{ind} + \varepsilon_{a_k} > 0\} \quad (15)$$

Where $\varepsilon_w, \varepsilon_{a_1}, ..., \varepsilon_{a_K}$, are independent standard normal disturbances. μ_0^w and $\mu_0^{a_k}$ are, respectively, the mean offered wage and a constant factors affecting the likelihood of amenity a_k provision. The first equation shows that observed wage offers $w^*(b, \text{car}_{occ}, \text{car}_{ind})$ are allowed to be affected by the amenities that a firm offers through the $(K \times 1)$ coefficient vector ρ, 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 $f(w^*, \mathbf{a}^*|.)$ and $\bar{F}_u(u|.)$. 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 $(w, \mathbf{a})$ as

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

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

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

$$\begin{aligned} l_{t+1} = {} & q^{ju_t}[1-\lambda_0]^{uu_t} \times \\ & \times \lambda_0^{uj_t} f_{t+1}(w_{t+1}, \mathbf{a}_{t+1}|.)^{uj_t} \times \\ & \times [1 - \lambda_1 \bar{F}(u_t|.) - \lambda_2 - q]^{s_t} \times \\ & \times [\lambda_1 \mathbf{1}\{w_{t+1} + \delta' \mathbf{a}_{t+1} > w_t + \delta' \mathbf{a}_t\} + \lambda_2]^{jj_t} f_{t+1}(w_{t+1}, \mathbf{a}_{t+1}|.)^{jj_t} \end{aligned} \tag{17}$$

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

$$l(.) = l_{t_0} \prod_{t=t_0}^{T} l_{t+1}(e_{t+1}, w_{t+1}, \mathbf{a}_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, w_t, \mathbf{a}_t, b, \text{car}_{occ}, \text{car}_{ind}) \tag{18}$$

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 $l_{t+1}(.)$ 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 $(w, \mathbf{a})$ across N individuals over T months between the year of entry and the fifth year on the labor market is

$$L(.) = \prod_{i=1}^{N} l_{t_0,i} \prod_{t=t_0}^{T} l_{t+1,1}(e_{t+1}, w_{t+1}, \mathbf{a}_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, w_t, \mathbf{a}_t, b, \mathrm{car}_{occ}, \mathrm{car}_{ind}) \qquad (19)$$

First, likelihood is divided in three parts: $L_1(\theta)$, $L_2(\theta, \lambda, \delta)$, $L_3(\theta, \lambda, \delta)$, where θ is the vector of all parameters of the unobserved job offer distribution F, λ is the vector of search frictions parameters and δ is the preferences parameters vector.
$L_1(\theta)$ corresponds to contribution to the likelihood of the density of job offers for workers who switch from unemployment to employment. $L_2(\theta, \lambda, \delta)$ includes the marginal likelihood of staying on the same job and switch jobs. $L_3(\theta, \lambda, \delta)$ collects all the remaining terms of the likelihood.

First, the part of the Likelihood that only depends on θ is isolated and parameters are estimated using the subsample of workers who move from non employment to employment.
Second, the estimated parameters $\hat{\theta}$ are substituted in $L_2(.)$ and $L_3(.)$ and a three-step procedure is used to estimate separately $\hat{\lambda}$ and $\hat{\delta}$.

1. A value δ_0 is guessed for δ. δ_0 is substituted in $L_2(.)$ and $L_3(.)$. Then $L_2(.) \times L_3(.)$ is maximized with respect to λ.

2. The estimated $\hat{\lambda}$ vector is substituted in $L_2(.)$ and $L_2(.)$ is maximized with respect to δ_1

3. The estimated $\hat{\delta}_1$ is used to repeat steps (1), (2) and (3) until convergence.

As Bonhomme & Jolivet (2009) discuss, the separate identification of search and preference parameters is made possible by the fact that the likelihood function represents the joint density of equilibrium wages and amenities for each period in the sample, accounting for transitions across labor market states. Hence, within-gender cross-workers differences in the outcomes of job moves (L_3) and in the probabilities of job moves (L_2) are both used for identification of λ and δ.
Specifically, given a guessed δ vector, the vector λ is estimated by using both the outcomes of job moves and the probability of moving across labor market states. However, once λ is fixed, only the probability of staying in one's current job or switching across jobs are used to estimate the preferences parameter vector δ. Hence, δ is identified because, given λ, the likelihood of a job to job move decreases in the utility of one's current job. Consequently, knowing w and the vector $\mathbf{a}$ for each employment relationship, each month, and each worker, together with $\hat{\lambda}$, the δ that maximizes the likelihood of observing the job change probability detected in the data identifies workers' utility parameters.

It is also relevant to notice that the preference parameters can be identified because the features of the job offer distribution are estimated separately using movements out of unemployment only. By estimating preferences and the characteristics of the job offer distribution separately it is possible to disentangle the impact of amenities on wages and utility due to workers' subjective evaluations from the impact of amenities on wages and utility due to differences in the labor demand that male and female workers face.

5 Results

5.1 Parameter Estimates

Tables 11, 12 and 13 report the structural parameter estimates. The tables also report asymptotic standard errors estimated through the outer product of gradients variance estimator, and the likelihood ratio tests p-Values. For each likelihood ratio test, the restricted likelihood is maximized by imposing that the parameter indicated by the respective column equals zero[16].

Regarding search frictions, the main difference emerging between male and female workers concerns the monthly probability of obtaining a job offer when unemployed. The probability is about 19% for women and 23% for men. This result is consistent across different specifications of the model and it is stable when allowing or not for within genders heterogeneity in terms of ability and career.

The result is particularly interesting in light of the descriptive evidence collected in Section 2.2. To the extent that male and female workers in the sample are similar in terms of labor market and work attachment during the time interval I consider in the structural analysis, it seems unlikely that the estimated difference in the probability of receiving job offers when unemployed can be ascribed to strong underlying differences in search effort when unemployed.

Male and female workers, instead, are predicted to face similar search environments when employed. The probability of receiving job offers (λ_1), of job destruction (q) and of constrained move (λ_2) are very similar across genders. In addition, all probabilities are very small. This is consistent with the use of monthly observations in the estimation.

Table 11: Estimated Search Frictions Parameters

	λ_0	λ_1	λ_2	q
		Females		
Coeff.	0.191	0.013	0.005	0.009
Asy.Std.Err.	(0.012)	(0.002)	(0.001)	(0.001)
		Males		
Coeff.	0.228	0.014	0.005	0.008
Asy.Std.Err.	(0.016)	(0.002)	(0.001)	(0.001)

National Longitudinal Survey of Youth, 1997. Asymptotic Standard Errors in parentheses.

Regarding preferences, the estimated results in Table 12 Panel (a) are perhaps partly surprising. While male workers are estimated to prefer working long hours more than female workers, the coefficient is positive for both genders. In addition, male and female workers are estimated to place similar weight on schedule flexibility and parental leave in their evaluation of job offers. Although the results for childcare show that preferences for this amenity are statistically indistinguishable from zero for both male and female workers, they should be interpreted cautiously given the very small number of jobs offering this amenity.

[16] Although I report asymptotic standard errors for completeness, I mostly rely on likelihood ratio tests to infer the statistical significance of the model parameters. The small number of individuals included in the estimation makes inference based on asymptotic standard errors problematic. The asymptotic likelihood ratio test is more powerful, hence more reliable in small samples.

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**			
	δ_f	δ_h	δ_l	δ_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:** $e^{-\delta_j}$			
	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 differences in preferences for amenities.

In Table 13 I report the results regarding the wage characteristics of the distribution of job offers that male and female workers face[17]. While these results should be interpreted cautiously due to the fact that labor demand is only modeled in reduced form, they suggest that the labor market prospects faced by male and female workers are highly dissimilar.

First, female workers are offered lower wages relative to male workers in all occupation and industry classes, unconditional of amenities provision. Regarding the latter, wages offered to male workers conditional on the provision of flexibility and parental leave are strictly higher than wage offers conditional on the absence of such benefits. Since flexibility and parental leave are the most relevant amenities from the point of view of workers' subjective evaluations, these

[17]The structural parameter estimates regarding the offer of amenities are reported in the Appendix.

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. While one might imagine that this result is driven by the stronger preferences of female workers for parental leave, I argue that this is unlikely. If preferences were reflected into wage-amenities offers, one would expect the wage premium associated to the provision of flexibility in male-specific job offers to be only slightly higher than the wage premium associated to the provision of flexibility in female-specific job offers. Instead, the estimated $\hat{\rho}^f$ shows that, while male workers successfully sort themselves into jobs paying higher wages and offering schedule flexibility, female workers tend to get lower wages when scheduled flexibility is provided. It suggests that constraints to workers' mobility across employers that specifically impact women play a role in determining the relation between wages and contractual benefits provision in the job offers that female workers obtain.

The evidence of wage premia attached to amenities that positively accrue to workers utility suggests that better and more productive firms are more likely to offer certain benefits and offer higher wages. This implication is fully consistent with the Hwang, Mortensen & Reed (1998) model. The lower wage premium, or wage losses, offered to female workers in association with the provision of certain amenities, instead, suggests that female workers may draw job offers from a distribution of employers whose productivity is lower relative to the productivity of employers offering jobs to male workers. In addition, it cannot be excluded that female labor supply is more rigid than male labor supply at the firm level. This idea, which is consistent with the observation that female workers tend to change job more often than men due to mobility or family constraints, implies that part of the difference between the wage and wage premia offered to men and women may arise due to monopsonistic discrimination.

Table 13: Estimated Wage Offer Parameters

	μ_0^w	μ_1^w	ρ^f	ρ^l	ρ^p	ρ^c	φ_e^w	φ_p^w	φ_o^w	φ_{fin}^w	φ_{tr}^2	φ_{oth}^w
							Females					
Coeff.	2.063	0.111	-0.011	-0.085	0.294	0.035	0.011	0.077	-0.453	0.068	0.278	0.119
Asy.Std.Err.	(0.553)	(0.124)	(0.080)	(0.1110)	(0.086)	(0.154)	(0.098)	(0.126)	(0.123)	(0.105)	(0.198)	(0.098)
LR Test p-Value	[0.000]	[1.000]	[0.4515]	[1.000]	[0.004]	[0.332]	[0.275]	[0.141]	[0.000]	[0.154]	[1.000]	[1.000]
							Males					
Coeff.	2.583	-0.034	0.121	-0.064	0.345	-0.048	0.188	0.324	-0.003	0.008	0.005	-0.065
Asy.Std.Err.	(0.974)	(0.221)	(0.106)	(0.104)	(0.115)	(0.263)	(0.140)	(0.137)	(0.137)	(0.159)	(0.176)	(0.141)
LR Test p-Value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[1.000]	[0.000]	[0.005]	[0.011]

National Longitudinal Survey of Youth, 1997.

5.2 Decomposing Utility from Employment Relationships

Once I estimate the model, I can use the estimated parameter vectors $\hat{\theta}$, $\hat{\lambda}$ and $\hat{\delta}$ to predict the steady state distribution of utility that employed workers obtain from their jobs and I can decompose the expected utility that workers obtain into different components. The decomposition of expected utility grounds on an asymptotic interpretation of the standard Oaxaca(1973)-Blinder(1973) decomposition.

In particular, the search model I estimate predicts that, given workers ability b and given occupation and industry classes, the expected utility from a job for a worker of gender $g = \{f, m\}$ is

$$
\begin{aligned}
E(u|g, b, \text{car}_{occ}, \text{car}_{ind}) &= E(w + \delta'\mathbf{a}|g, b, \text{car}_{occ}, \text{car}_{ind}) \\
&= \mu_0^g + \mu_1^g b + \sum_{occ=1}^{3} \varphi_{occ}^{g,w}\text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,w}\text{car}_{ind} + \\
&+ \sum_{k=1}^{4} \rho_k^g \text{P}(a_k^{of} = 1|g, b, \text{car}_{occ}, \text{car}_{ind}) + \sum_{k=1}^{4} \delta_k^g \text{P}(a_k^{of} = 1|g, b, \text{car}_{occ}, \text{car}_{ind}) \\
&= \mu_0^g + \mu_1^g b + \sum_{occ=1}^{3} \varphi_{occ}^{g,w}\text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,w}\text{car}_{ind} + \\
&+ \sum_{k=1}^{4} \rho_k^g \Phi\left(\mu_0^{g,a_k} + \mu_1^{g,a_k} b + \sum_{occ=1}^{3} \varphi_{occ}^{g,a_k}\text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,a_k}\text{car}_{ind}\right) + \\
&+ \sum_{k=1}^{4} \delta_k^g \Phi\left(\mu_0^{g,a_k} + \mu_1^{g,a_k} b + \sum_{occ=1}^{3} \varphi_{occ}^{g,a_k}\text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,a_k}\text{car}_{ind}\right) \qquad (20)
\end{aligned}
$$

Using the estimated parameters of the model, the difference in the expected utility that female and male workers with the same ability level obtain from jobs can be decomposed as

$$
\begin{aligned}
\hat{E}(u|f, .) - \hat{E}(u|m, .) &= \left[(\hat{\mu}_0^f + \hat{\varphi}_j^{f,w} + \hat{\varphi}_\tau^{f,w}) - (\hat{\mu}_0^m + \hat{\varphi}_j^{m,w} + \hat{\varphi}_\tau^{m,w})\right] + (\hat{\mu}_1^f - \hat{\mu}_1^m)b + \\
&+ \sum_{k=1}^{4} \hat{\rho}_k^m \left[\hat{\Phi}^f(.) - \hat{\Phi}^m(.)\right] + \sum_{k=1}^{4} \hat{\Phi}^f(.) \left(\hat{\rho}_k^f - \hat{\rho}_k^m\right) \\
&+ \sum_{k=1}^{4} \hat{\delta}_k^m \left[\hat{\Phi}^f(.) - \hat{\Phi}^m(.)\right] + \sum_{k=1}^{4} \hat{\Phi}^f(.) \left(\hat{\delta}_k^f - \hat{\delta}_k^m\right) \qquad (21)
\end{aligned}
$$

The left-hand side of the first line of equation (21) represents the difference in the average utility from jobs between female and male workers of ability level b, occupation j and sector τ. The first line on the right-hand side represents the contribution to the utility gap (if any) coming from differences in the career-specific mean offered wage and in the mean estimated return to ability.

On the second and third line, the first elements represent the contribution to the utility gap due to gender-specific selection of workers into jobs offering amenity 1 to 4, that is: flexibility, long hours, unpaid/paid parental leave, and child care.

The second element on the second line shows the contribution to the utility gap due to gender-based differences in the wage gain or loss associated to the provision of a certain amenity in the job offer distribution. Specifically, it shows by how much the predicted utility that women obtain from their employment relation would rise or fall relative to men if the female job offer 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 utility gap. This occurs mechanically to the extent that more women than men work in firms offering contractual benefits that positively accrue to workers' utility.

While the partial equilibrium nature of the estimation procedure I apply calls for caution in interpreting its findings, the results are of particular interest. First, they show that young, labor market attached, and highly educated employed male and female workers encounter similar labor market frictions, and are similar in terms of preferences for job-specific contractual benefits. In particular, the young women in my sample do not appear to be willing to pay strictly more than young men, out of their wages, in order to obtain benefits such as flexibility in working schedule and parental leave. At the same time, women in most careers receive wage offers that penalize them relative to their male counterparts. Such pay penalties, that translate into overall welfare penalties, are further exacerbated when amenities such as flexible schedule and parental leave are provided. It suggests that young women may face constraints to mobility across jobs, likely due to current or anticipated family responsibilities, that in fact lower their bargaining power, and that employers may account for.

6 Conclusions

In this paper I studied a recent generation of young, college graduate workers entering the United States labor market since year 2000, and investigated gender based differences in job search rigidity, preferences for job-specific attributes, and features of the job offers that workers receive. First, the descriptive analyses I performed showed that a gender pay gap in early careers arises and increases in spite of strong similarities in workers' human capital and labor market attachment, and that job changes play a non negligible role in explaining it. I also showed that, controlling for a number of individual and job specific characteristics, job search and job changes entail significant wage gains for male workers solely, while female workers only experience wage losses following constrained job transitions. Finally, I used the estimation of quit rates to show that female workers' labor supply is more sensitive to the provision of schedule flexibility and parental leave, and that, given their current wages, women have lower chances than men to improve their pay even more by climbing the job ladder.

Second, by estimating a model of hedonic job search that implements the methodology proposed by Bonhomme & Jolivet (2009), and grounds on the theoretical work of Hwang, Mortensen & Reed (1998), I quantified the extent to which men and women differ along the three dimensions mentioned above. The model estimates suggest that young, highly educated male and female employed workers are 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 offer distribution that women face, instead, differs from the male-specific job offer distribution remarkably. Women tend to be offered low wages and obtain lower wage gains relative to men (or even wage losses) when contractual benefits are provided. Wages and amenities-related wage penalties strongly affect the predicted male-to-female gap in utility that workers obtain from jobs in early careers. In fact, given similar preferences for amenities across genders, job-specific attributes are provided at a wage cost for women relative to men.

While data limitations do not allow to investigate gender differences in job offers further, it would be interesting to study the employers' decisions in terms of amenities provisions and wages by using firm-level data, and to analyze their impact on workers of different genders, in line with the recent work by Goldin, Kerr & Olivetti (2020).

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Appendix

A1. Detailed Dataset Construction

In this section I describe in greater detail the construction of the sample of highly skilled and strongly labor market attached workers I studied.

A1.1 Information of Interest

Background and Demographic Information concerns the initial characteristics of the individuals in the sample. It includes gender, race and ethnicity, detailed date of birth (year, month, day), citizen status, family composition, family income and parental education background.

Education Information regards each individual's educational achievement and the timing of his/her educational steps. For each individual, I retain two kinds of information: year-specific information and education achievement as of Round 17. In particular, for each individual I retain his/her enrollment status in each year. Also, looking backward to all the education information available by Round 17, I keep track of the year in which individuals in the sample left (if any) education, the year when they left high school, whether they obtained a high school degree or a GED certificate, whether and in which year they enrolled in college, whether and in which year they obtained an Associate Degree, a Bachelor Degree, a Master or a PhD Degree.

Family Formation and Fertility Information includes data about the timing and number of marriages (if any), the timing of childbirth and the total number of children each individual has in each year.

Labor Market Information is divided between:

a. Information pertaining to each single week since week 1 in 1999, the first available date, to the last available week in 2016;

b. Information pertaining to an year;

c. Information pertaining to each job that a worker performed in each year.

Concerning point *a.*, week-specific information about employment status is available in the NLSY weekly arrays. Here, employment status is reported for each week of each year from 1999 to 2016. It is possible to disentangle whether, in each week, an individual was unemployed, out of the labor force, in active military service or employed. For employed workers, the survey provides the unique identifier of the employer where the individual works.

Regarding point *b.*, the NLSY provides information about the total number of jobs, weeks worked and hours worked in each year. I use this information mainly to check the correctness of the variables I construct.

Regarding point *c.*, detailed information about job and employer characteristics is available. I retain information about all available jobs. This information is collected once for each round and does not change within a year. For each job, the NLSY provides a person-specific unique identifier that allows to match the characteristics of each job to all weeks in which the workers 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 employed or in an employee job, whether the worker is covered by a union-bargained contract.

Furthermore, information about the total number of days of entitled paid vacation, sickness or family absence and about available benefits is provided for all employees and self-employed workers. Possible available benefits include: medical insurance, life insurance, dental care, stock options, paid and unpaid parental leave, childcare, flexible schedule, partial or full education tuition refund and retirement plans.

Finally, the survey collects some information about the employer, including its size in terms of number of employees, whether or not an employer operates at more than one location and the estimated number of workers at different locations (if any).

A1.2 Merging Data

I retain the information of interest in different datasets which are either year- week- or job-specific. First, I merge year-specific labor market information and personal information to the weekly arrays using the unique person-specific identifier and year as merging variables. In a second step, I merge job-specific information with the weekly arrays, using the person-specific and the person-job-specific identifier and year as merging variables.

Imputations

Mismatch between Actual and Reported Begin of Employment Relationship

It is important to notice that, although most weeks can be merged with job-specific information, some imputations are required. Some weeks cannot be merged for the following two reasons:

a. A worker started a certain employment relationship in a certain year t and after round t interview, so that the job was first reported by the worker in year $t+1$ or, for reasons that cannot be tracked, in some year $t+k$;

b. A worker started a certain employment relationship in a certain year t and although, according to the weekly-array data, he/she kept the employment relationship in some following year(s), the worker did not report job-specific information in successive round interviews.

Two things are worth noting. First, week-job-specific information must be imputed for all weeks in survey years 2010, 2012, 2014 and 2016, since interviews were not conducted in those years. In my data, years indicate round so that, even if a Round 17 (2015-16) interview was 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, I impute all the job-specific information from the first successive year when a certain job was reported. For data falling in case b., I impute all the job-specific information from the first past year when a certain job was reported.

Missing Values from Errors in Reporting When possible, I also impute job-specific information when it is missing but the interview was administered to the worker and the worker was supposed to report information. In order to do that, I impute the closest-in-time job/employer specific information.

A specific categorical variable is created in order to keep track of the different types of imputation performed.

Employed Workers with 0 \$ Wages I impute wages for these workers as well in order to have the logarithm of wage defined. I proceed by computing the minimum wage observed for workers of the same gender and being in the labor market since the same number of years as the worker who reports a 0 \$ wage. Then, I assign this year of experience and gender specific minimum wage to the 0\$ wage reporting worker.

The merged sample consists of about 8 million worker-week cells. For each worker I only maintain one observaion for each employment-spell and proceed in cleaning the data as described in Section 2.

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

$$\begin{aligned} y^*_{ijt} &= z'_{ijt}\xi + \nu_i + u_{ijt} \\ &= \alpha + \beta w_{it} + \gamma \mathbf{I}\left[\text{Parental Benefits}_{ijt}\right] + \delta \mathbf{I}\left[\text{Flexible Schedule}_{ijt}\right] + x'_{ijt}\eta + \nu_i + u_{ijt} \end{aligned} \tag{22}$$

$$y_{ijt} = \mathbf{I}\left[j(t) \neq j(t+1)\right] = \mathbf{I}\left[y*_{ijt} \geq 0\right] \tag{23}$$

$$\Pr\left[y_{ijt} = 1 | z_{ijt}, \nu_i\right] = \frac{\exp\{z'_{ijt}\xi + \nu_i\}}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \tag{24}$$

Table 16 reports the vector of estimated $\hat{\xi}$. As shown by Chamberlain (1980) and Wooldridge (2002) $\hat{\xi}$ 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 $\Pr\left[y_{ijt} = 1 | z_{ijt}, \nu_i\right]$ 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

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

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

Now, let $z'_{ijt} = [z^1_{ijt}, ..., z^K_{ijt}]$ and suppose that for some k, $z^k_{ijt} = \ln(Z^k_{ijt})$. Then

$$\begin{aligned} \eta^{Z^k}_{ijt} &= \frac{\partial p_{ijt}}{\partial Z^k_{ijt}} \frac{Z^k_{ijt}}{p_{ijt}} \\ &= \xi_k \frac{1}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \\ &= \xi_k \left(1 - p_{ijt}\right) \end{aligned} \tag{27}$$

Kitazawa (2012) shows that the mean elasticity of the p_{ijt} with respect to Z^k_{ijt} can be consistently estimated as

$$\bar{\eta} = \hat{\xi}_k \left(1 - \bar{y}\right) \tag{28}$$

Where $\hat{\xi}_k$ is a consistent estimator for ξ_k, such as the conditional logit estimator, and $\bar{y} = T^{-1} N^{-1} \sum_{t=1}^{T} \sum_{n=1}^{N} y_{ijt}$.

Analogously, let $z^k_{ijt} = Z^k_{ijt}$ and Z^k is a continuous real valued variable. Then the semi-elasticity of p_{ijt} with respect to Z^k_{ijt} is

$$\begin{aligned} \zeta^{Z^k}_{it} &= \frac{\partial p_{ijt}}{\partial Z^k_{ijt}} \frac{1}{p_{ijt}} \\ &= \xi_k \frac{1}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \\ &= \xi_k \left(1 - p_{ijt}\right) \end{aligned} \tag{29}$$

Implying that mean semi-elasticities can be consistently estimated using the same estimator as above. Finally, suppose that z^k_{ijt} is a dummy variable. Then, letting $p^1_{ijt} = \Pr[y_{ijt} = 1 | z^1_{ijt}, ...,$ $z^k_{ijt} = 1, ..., z^K_{ijt}, \nu_i]$ and $p^0_{ijt} = \Pr\left[y_{ijt} = 1 | z^1_{ijt}, ..., z^k_{ijt} = 0, ..., z^K_{ijt}, \nu_i\right]$ the percentage change in

p_{ijt} when z_{ijt}^{k} goes from 0 to 1 can be written as

$$\begin{aligned}\frac{p_{ijt}^{1}-p_{ijt}^{0}}{p_{ijt}^{0}} &= \left(\exp\{\xi_k\}-1\right)\frac{1}{1+\exp\{z_{ijt}'\xi+\nu_i\}} \\ &\approx \xi_k\left(1-p_{ijt}^{1}\right)\end{aligned} \tag{30}$$

Where the last line holds because $e^{\xi_k}-1\geq\xi_k$ for all $\xi_k\in R$, with equality when $\xi_k=0$. Hence, $e^{\xi_k}-1\approx\xi_k$ for small enough ξ_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*
	(0.2572)	(0.2367)
Total Number of Spells out of Lab.Force by t	-0.3754***	-0.5490***
	(0.1011)	(0.0940)
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 characteristics at time t: 9 occupation and 11 industry dummies, three dummies indicating whether the unemployment rate in the US region where the workers resides at t is medium-low, medium or high.

A4. Structural Parameter Estimates: Amenities Offered

Table 17: Estimated Flexible Schedule Parameters

	μ_0^{fl}	μ_1^{fl}	φ_e^{fl}	φ_p^{fl}	φ_o^{fl}	φ_{fin}^{fl}	φ_{tr}^{fl}	φ_{oth}^{fl}
				Females				
Coeff.	0.249	-0.106	0.344	0.594	0.683	0.030	-0.187	-0.429
Asy.Std.Err.	(1.597)	(0.371)	(0.285)	(0.367)	(0.388)	(0.297)	(0.468)	(0.345)
LR Test p-Value	[0.458]	[0.253]	[0.002]	[0.256]	[0.093]	[0.843]	[1.000]	[1.000]
				Males				
Coeff.	1.743	-0.449	0.211	0.574	0.341	-0.196	0.355	-0.023
Asy.Std.Err.	(2.173)	(0.498)	(0.365)	(0.395)	(0.316)	(0.398)	(0.493)	(0.355)
LR Test p-Value	[1.000]	[1.000]	[0.000]	[0.000]	[0.000]	[0.013]	[0.009]	[0.000]

National Longitudinal Survey of Youth, 1997.

Table 18: Estimated Long Hours Parameters

	μ_0^{lh}	μ_1^{lh}	φ_e^{lh}	φ_p^{lh}	φ_o^{lh}	φ_{fin}^{lh}	φ_{tr}^{lh}	φ_{oth}^{lh}
				Females				
Coeff.	-3.219	0.541	-0.203	0.212	-1.005	0.017	1.178	-0.085
Asy.Std.Err.	(1.860)	(0.431)	(0.327)	(0.368)	(0.841)	(0.349)	(0.545)	(0.340)
LR Test p-Value	[0.016]	[0.073]	[1.000]	[0.155]	[0.001]	[1.000]	[0.004]	[0.512]
				Males				
Coeff.	-1.922	-0.352	0.395	0.030	0.245	-0.733	-1.036	-0.377
Asy.Std.Err.	(3.177)	(0.719)	(0.462)	(0.457)	(0.431)	(0.455)	(0.793)	(0.409)
LR Test p-Value	[0.000]	[1.000]	[0.000]	[0.033]	[0.083]	[0.014]	[0.000]	[0.000]

National Longitudinal Survey of Youth, 1997.

Table 19: Estimated Parental Leave Parameters

	μ_0^{pl}	μ_1^{pl}	φ_e^{pl}	φ_p^{pl}	φ_o^{pl}	φ_{fin}^{pl}	φ_{tr}^{pl}	φ_{oth}^{pl}
				Females				
Coeff.	1.916	-0.275	0.466	0.328	-0.161	-0.665	-0.236	-0.606
Asy.Std.Err.	(1.951)	(0.450)	(0.292)	(0.422)	(0.332)	(0.319)	(0.419)	(0.301)
LR Test p-Value	[0.172]	[0.314]	[1.000]	[0.301]	[1.000]	[1.000]	[0.212]	[1.000]
				Males				
Coeff.	-0.825	0.262	0.393	0.183	-0.572	-0.642	0.454	-0.009
Asy.Std.Err.	(2.290)	(0.518)	(0.399)	(0.423)	(0.330)	(0.356)	(0.512)	(0.337)
LR Test p-Value	[1.000]	[0.006]	[0.604]	[0.002]	[0.000]	[1.000]	[1.000]	[0.087]

National Longitudinal Survey of Youth, 1997.

Table 20: Estimated Childcare Parameters

	μ_0^{cc}	μ_1^{cc}	φ_e^{cc}	φ_p^{cc}	φ_o^{cc}	φ_{fin}^{cc}	φ_{tr}^{cc}	φ_{oth}^{cc}
				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)	(.)	(0.632)	(1.146)	(0.531)
LR Test p-Value	[1.000]	[0.003]	[1.000]	[0.001]	[1.000]	[0.248]	[0.002]	[0.000]

National Longitudinal Survey of Youth, 1997.