Are We There?
The Search for Amenities and the Early-Career Gender Wage Gap

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Abstract

I study the contribution of search frictions, preferences for amenities (flexibility and parental leave), and wage offers to the early career gender pay gap among US college graduates. Using data from the NLSY97, I document that highly educated *Millennial* women earn \$1.80 less than men, per hour, by five years since labor market entry, irrespective of their marital and parental status, largely due to gender-differences in wage gains from job changes. Motivated by this evidence, I estimate a structural model that allows to disentangle the impact of the main determinants of returns to job changes, that is, search frictions, preferences for amenities, and wage offers on the pay gap. I find that young men and women share similar preferences for amenities. Compared to men, however, women are offered lower wages, and predominantly so in jobs that provide benefits. Since these jobs typically offer higher wages too, the gender pay gap expands as workers climb the job ladder to enter employment relationships that offer better wage-benefits bundles. The higher price that women pay for amenities explains 42% of the early-career growth in the wage gap in the model. The remaining portion is explained by the lower wages offered to women in jobs that do not provide benefits (25%) and by women's stronger search frictions (33%).

JEL Codes: J16, J31, J32, J64
Keywords: Gender wage gap, nonwage benefits, job search, early careers.

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1 Introduction

An extensive literature documents many of the determinants of the wage gap between men and women, but residual gender wage differences remain even within narrowly defined categories of workers (Blau & Kahn 2017). Among highly educated workers in particular, wages do not differ by gender at labor market entry, but the pay gap arises during workers' early careers (Manning & Swaffield 2009) and increases over time in the labor market (Barth, Olivetti & Kerr 2021). While childbirth events and the consequent decrease in women's labor supply play a crucial role in determining the expansion of the gender wage gap (Cortes & Pan 2019, Bertrand, Goldin & Katz 2010, Light & Ureta 1995), they do not fully explain it.

In this paper I document that gender differences in wage gains from job changes also play a major role in explaining the early career pay gap between highly educated men and women. Furthermore, I disentangle the contribution of the main determinants of gender differences in wage gains from job changes, namely, search frictions, wage offers received by workers, and preference for job-specific amenities to the increase in the gap over time in the labor market.

The joint analysis of the impact of search frictions, wage offers, and preferences on the early career pay gap is necessary to understand the nature of the phenomenon. On the one hand, during workers' early careers, wages tend to grow through job search and job changes (Topel & Ward 1992). If women receive fewer job offers due to stronger search frictions (Bowlus 1997), or if the wage offers they receive are less lucrative than the wage offers men receive (Light & Ureta 1992), the wage gap arises and expands due to the constraints that women face when climbing the job ladder (Barth & Dale-Olsen 2009, Hirsch 2010, Manning 2003) and that depress the utility that women obtain from their employment relationships, compared to men.[1] On the other hand, workers' decision to change job depends on their valuation of both wage and non-wage amenities (Hwang, Mortensen & Reed 1998). Women may accept stronger wage cuts when changing job in exchange for the provision of amenities if they prefer certain benefits more strongly than men. If so, the wage gap arises and expands due to compensating wage differentials: while accepting lower wages when offered amenities, women obtain same utility as men from their jobs.

While preferences for amenities may matter in determining the gender pay gap,[2] in a frictional labor market, conditional on the provision of amenities, women may still earn lower wages than men with virtually identical preferences. To see this, notice that more productive employers offer higher wages and may find it less costly to provide non-wage benefits that are valuable to their

[1]Intuitively, firms set wages to attract and retain workers (Burdett & Mortensen 1998). If women's job choices are constrained, as an example by current or anticipated family responsibilities, or by mobility costs, then firms' can offer lower wages to women and still be able to attract and retain them.

[2]As an example, Flabbi & Moro (2012) estimate that college graduate women have strong preferences for part-time work and speculate that women's willingness to forgo some wage gains to work few hours may explain the pay gap between highly educated male and female workers. While they do not estimate men's preferences, Mas & Pallais (2017) show that female workers prefer jobs that enhance work-life balance more strongly than male workers, but do not find that preferences for amenities explain a significant portion of the pay gap in their data.

employees (Hwang, Mortensen & Reed 1998). Consequently, both male and female workers who are provided amenities are likely to be observed in higher-pay jobs that they progressively access as they climb the job ladder.[3] Yet, if women face stronger search frictions or are offered lower wages in amenity-providing jobs compared to men, the gender pay gap increases as workers search for jobs offering better wage-amenities bundles, even though men's and women's preferences for amenities may not differ. In other words, the search for jobs that provide amenities may explain the opening and expansion of the pay gap due not only to differences across genders in preferences for amenities, but also to differences in search frictions and in the wages offered to men and women in amenity-providing jobs.

In the first part of this paper, using data from the National Longitudinal Survey of Youth 1997 (NLSY97), I characterize the early-careers of *Millennial* college graduates and document that the search for amenities matters in explaining the early career pay gap. First, I show that both wages and the shares of men and women in jobs that provide amenities increase over years of labor market experience. It suggests that workers take non-wage benefits into account when changing job, and that their progressive entry into *better* jobs involves higher pay and better benefits packages. Second, I show that a gender wage gap arises approximately three years after labor market entry, reaching 3.9 log-points by the fifth year of labor market experience, between male and female workers who are similarly -and strongly- committed to work, irrespective of women's marital and parental status. Accounting for heterogeneity in the reasons determining job changes and in jobs' characteristics, I provide evidence that the first job change, occurring on average during the third year of labor market experience for both men and women, determines 60% of the hourly gender pay gap observed by the fifth year in the labor market.[4]

[3] According tho the hedonic theory of compensating wage differentials originated by Rosen (1974), in a competitive labor market equilibrium with workers of equal ability and firms of equal productivity, workers with strong preferences for a valuable amenity accept wage cuts in exchange for the provision of the amenity. The consequent cross-sectional correlation between valuable benefits and wages in equilibrium is negative. Conversely, the cross-sectional correlation between the equilibrium quantity of a certain *disamenity* and workers' wages is positive. In other words, workers pay out of their wages to obtain utility-enhancing job characteristics, and are compensated for negative job characteristics through higher wages. The literature provided evidence that this implication is largely counterfactual. Hwang, Reed & Hubbard (1992) noted that the OLS estimation of workers' preferences for job attributes through the cross-sectional relation between wages and amenities leads to substantial biases due to workers' unobserved heterogeneity in ability. As high-ability workers self-select into jobs providing both higher wags and valuable amenities, cross-sectional estimates of compensating differentials are often close to zero and at times have opposite sign relative to what the hedonic theory would imply. The lack of empirical evidence on compensating differentials is further exacerbated when workers' preferences for amenities are inferred through hedonic wage regressions using panel data, the latter allowing to control for unobserved workers' heterogeneity in ability (Brown 1980). Taken face value, these results could be interpreted as evidence that workers, acting in a perfectly competitive labor market, do not have strong preferences for non-wage benefits. Yet, as employee-level panel data hedonic regressions cannot control for productivity heterogeneity across employers, the resulting negligible compensating differential estimates can be biased toward zero if, over their own life-cycle, workers' search and progressively obtain more productive jobs offering both higher wages and better amenities. The latter view is consistent with the idea that the labor market is in fact frictional and non competitive. A number of authors showed that the difficulty in finding evidence of compensating wage differentials through reduced-form wage regressions, indirectly suggests that labor market imperfections exist (Lang & Majumdar 2004), and that search dynamics affect workers' labor market outcomes (Bonhomme & Jolivet 2009, Hwang, Mortensen & Reed 1998, Lavetti & Schmutte 2018). Khandker (1988) was the first to introduce non-wage job attributes in a sequential search model.

[4] I also show that the results qualitatively hold when comparing workers who are not married and who do not have children either by the time they change job or by the last available wave of the NLSY97.

The evidence that returns to job changes differ across genders and explain a large portion of the early career pay gap is consistent with three different hypotheses. First, the evidence suggests that women may receive lucrative job offers at a lower rate compared to men (Bowlus 1997), hence facing stronger search frictions and fewer chances to climb the ladder. Second, it hints that men may draw offers from a *better* wage offer distribution (Light & Ureta 1992), that is, from a distribution that first order stochastically dominates the distribution of wages offered to women. Third, it is consistent with the idea that women may have stronger preferences for certain non-wage benefits, thus being more willing than men to accept low wage offers in exchange for their provision.

Descriptive analyses, however, do not allow to quantify either the extent of such differences (if any), or the contribution of the three aforementioned factors to the early career pay gap. Search frictions, job offers, and preferences for amenities are ultimately unobserved. For this reason, in the second part of the paper, I rely on a structural model of hedonic job search to estimate gender differences in preferences for amenities, search frictions and wage-amenities offers, and to quantify their impact on the early career pay gap and on its increase over years of experience. In the model, workers' utility depends on wages and on the amenities 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. I further allow job offers to be heterogeneous based on workers' ability and on their careers, proxied by aggregate occupation and industry classes. The model builds upon the Bonhomme & Jolivet (2009) model, a partial equilibrium version of the Hwang, Mortensen & Reed (1998) hedonic model of job search.

Crucially, the model's estimation allows to separately identify preferences for amenities and the wage offers that workers receive in amenity-providing jobs using data that provide high-frequency information on workers' transitions both across labor market statuses and across employers, such as the NLSY97. Intuitively, the features of the distributions of jobs offered to men and women can be identified using the wage and amenities outcomes of workers entering a job from unemployment. In a search labor market equilibrium, all employers offer at least workers' reservation utility in order to attract employees (Burdett & Mortensen 1998, Hwang, Mortensen & Reed 1998). Consequently, unemployed workers accept any job offer, and their preferences for amenities do not impact their choices. Given the distribution of wages offered to men and women, workers' preferences for amenities and search frictions can be identified through the changes in wage-amenities bundles experienced by workers undergoing a job-to-job transition between two consecutive periods.

In the model I focus on the impact on wages of amenities that are especially valuable to young workers with strong labor market attachment: flexible schedule and parental leave. While the value of these benefits for US workers is testified by the persistency of intense debates around work-life balance and by the rising share of firms offering flexibility and parental leave in an effort to attract and retain employees,[5] the provision of these benefits may differently impact the wages paid to young men and young women. On the one hand, women may prefer these amenities more strongly than men, thus being willing to accept wage cuts when changing jobs in exchange for their provision. On the other hand, young women may be somehow constrained to choose among jobs offering some form of work-life balance enhancing amenity. This is likely to happen if, for example, young women perceive benefits such as flexibility and parental leave as an indirect form of employment insurance in the (possible) event of a childbirth.[6]

The model estimates show that young, highly educated male and female employed workers share similar and strong preferences for job attributes such as flexibility and parental leave. Due to the high value attached to the provision of flexibility and parental leave, the average full-time full-year woman in my sample is predicted to earn approximately $3000 dollars less during her early career, than she would if she did not value non-wage benefits. Workers' preferences, however, are so similar across genders that they do not determine the early career pay gap. Conversely, I estimate that women find it harder to climb the job ladder. First, I find that search frictions are overall stronger for women: even labor market attached young women are 13% less likely than men to obtain job offers when out of work. Second, I estimate that the job offers that workers receive are remarkably different across genders. Women receive offers entailing lower wages relative to men, and increasingly so when employers provide parental leave and schedule flexibility.

Noticeably, I estimate that employers offering benefits also tend to pay higher wages to their employees so that, as workers climb the job ladder to search for amenities, wages increase for both men and women. Due to the lower wage offered to female workers in amenity-providing jobs, however, women face lower wage-growth prospects through job search compared to men. As a consequence, the gender pay gap expands. The lower wage offers received by women in jobs that provide valuable benefits explains 42% of the early career increase in the pay gap that the model predicts. The residual portion of the wage gap growth is explained by gender-differences in search frictions (33%) and by the lower wages that women are offered in jobs that do not provide benefits (25%).

Since women are offered lower wages and pay a higher price for the provision of amenities relative to men in spite of similar preferences, women's overall utility from employment rela-

[5] See, for example, Olga Khazan, "Give Up on Work-Life Balance", *The Atlantic* May 30 2019, Sarah Halzack "Workplace Flexibility Can Be Key to Recruiting and Retaining Top Workers", *The Washington Post* December 2 2012 and Claire Cain Miller, "Walmart and Now Starbucks: Why More Big Companies Are Offering Paid Family Leave", *New York Times* January 24, 2018.

[6] This reasoning is mostly salient 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. Only in April 2021, under the "American Families Act", the US President Joe Biden proposed a plan to finance the provision of 12 yearly weeks of paid parental leave to American workers. For an assessment of the most recent litarature and cross-country evidence on parental leaves, see Olivetti & Petrongolo (2017).

tionships is lower than men's, and predominantly so in jobs that offer flexibility and parental leave. In other words, the model I estimate provides evidence that the early career gender pay gap does not arise as a consequence of compensating wage differentials.

These results are relevant from a policy perspective, as they hint that policies subsidizing employers' cost of providing certain valuable benefits (e.g. parental leave) may help reduce the gender pay gap, by expanding the set of jobs that women may draw their wage offers from. The proposal to fund 12 weeks of paid parental leave for all eligible American workers that the US President Joe Biden mentioned in March 2021, when introducing the "American Families Plan", goes in this direction.

The paper is structured as follows. In section 2, I explain the contribution of this paper to the related literature. Section 3 describes the data and sample selection and illustrates the main characteristics of the workers I study. In section 4, I illustrate the descriptive analyses that motivate this work. Section 5 explains the search model and its estimation. In section 6, I show the estimation results and use the estimated structural parameters of the model to decompose the early career gender wage gap and its growth path. Section 7 concludes.

2 Related Literature

This paper's contribution to the literature studying the gender pay gap is twofold. First, I provide a comprehensive analysis of the evolution of the pay gap during the early careers of *millennial* American workers. By focusing on this recent cohort, I contribute to updating the 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 *baby-boom* workers during the 1990s. Second, building on the 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, I contribute to the literature by accounting for the role of certain valuable amenities in determining the early career pay gap.

Two recent works by Liu (2016) and Amato-Patiño, Baron & Xiao (2020) are closely related to this paper. Liu (2016) is the first to acknowledge the need to distinguish between workers' preferences and available wage offers in analyzing the gender pay gap among young workers. Building on previous work by Bowlus & Grogan (2009), Liu (2016) uses the Survey of Income and Program Participation (1996) to estimate an hedonic search model allowing both for gender-based differences in labor market attachment and in preferences over part-time and full-time work, and for differences in the wages offered to male and female workers. He finds that the latter explain 65% of the pay gap.

This work expands on his contribution in two ways. First, by leveraging the unique features of NLSY97 data, I can neatly reconstruct workers' employment history since labor market entry and uncover the role that on-the-job amenities and contractual benefits play in determining not only the average gender wage gap but also, crucially, its opening and growth throughout workers' early careers. Second, I net out of my analysis any gender differences in factors whose analysis is at the core of Liu (2016) contribution by focusing on men and women who are strongly attached to the labor market and who typically work full-time throughout their early careers. By doing so, I show that a wage gap exists since the very beginning of workers' careers even between men and women who are virtually identical along these dimensions. Hence, I complement Liu (2016) contribution by showing the strong impact on the pay gap of the price of job characteristics that are valuable to those *millennials* who are strongly committed to continuously work full-time: schedule flexibility and parental leave.[7]

This paper and its findings are also related to a recent contribution by Amato-Patiño, Baron & Xiao (2020). The authors study the early careers of a US representative sample of *baby-boom* workers using NLSY79 data, and estimate a life-cycle model of job search and human capital accumulation. They find that wage setting practices are the main determinant of the gender pay gap at the beginning of workers' careers, while gender-based differences in human capital accumulation contribute to the expansion of the wage gap later in the life-cycle. In their model, wage setting determines the gap at labor market entry, as employers statistically discriminate against female workers if they expect the latter to experience future career interruptions and consequent low rates of on-the-job human capital accumulation.

As previously mentioned, I find that a pay gap arises among strongly labor market attached workers since labor market entry, well before any gender-based difference in labor force participation arises. I also show that differences in wage offers determine the bulk of the early career pay gap, and predominantly so when employers offer schedule flexibility and parental leave. As such, my findings can be interpreted in two ways. On the one hand, they may provide some indirect evidence that the mechanisms determining the pay gap among the *baby-boom* workers analyzed by Amato-Patiño, Baron & Xiao (2020) can also be relevant in understanding the persistent gender pay gap among *millennials*. As a matter of fact, employers offering flexibility and parental leave may be particularly prone to statistically discriminate against female workers if they expect the latter to have future higher take-up rates of parental leave days or of flexible work arrangements relative to male workers. On the other hand, my findings do not allow to rule out that gender differences in wage offers at the very beginning of workers careers' are mostly due to pure monopsonistic discrimination. It is not implausible to imagine that women's labor market attachment may decrease over time in the labor market, if they face more unfavorable labor market conditions relative to men soon after labor market entry, in spite of their equal

[7] My findings provide some suggestive evidence that firm-specific wage setting practices may matter in explaining the residual gap in wages. This topic has been explored in depth by the literature studying wage dispersion across firms, monopsony and monopsonistic discrimination (Card, Cardoso & Kline 2016, Card, Cardoso, Heining & Kline 2018, Manning 2003).

preferences and commitment to work. Furthermore, I observe that young, college graduate men and women are similarly likely to change at least one job by the fifth year of labor market experience, and do so after a similar number of years of tenure. Transitions across labor market statuses are equally comparable across genders at the beginning of workers' careers. In light of this evidence, it is not clear that workers' early-career employers' should expect women to quit their jobs at higher frequencies, thus statistically discriminating against them.

3 Data

3.1 Features of the NLSY97 and Sample Selection

I use data from the National Longitudinal Survey of Youth 1997 (NLSY97), a nationally representative panel including 8984 young male and female Millennials born between 1980 and 1984. 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 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 allows to cleanly construct workers' career dynamics since labor market entry and workers' movements across jobs.

The sample I study in this paper includes a subgroup of non African-American and non Hispanic highly educated workers, who assiduously participate to the labor market and whose careers can be observed for five to ten years since labor market entry.[8]

In order to reconstruct workers careers' trajectories, 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 per year (Loprest 1992) 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.[9] For each worker, I retain information regarding at most the first ten years in the labor market and require each worker to be followed for at least the first five years of labor market experience. Hence, I drop all individuals who entered the labor market from 2013 on. I further restrict the sample to individuals with strong labor market attachment, 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 drop workers who are self-employed in at least one year, individuals who report unreasonably high hourly wages (i.e. wages above 200$ per hour in 2005 US dollars) or unreasonably high weekly hours worked (i.e. more than 112 hours per week) at least once, and workers who ever report being employed in agricultural occupations or in the military. As a final

[8]In the Appendix, I provide evidence that the characteristics of the sample of interest and most results are qualitatively unaffected when I include workers of all races and ethnicities.

[9]This definition implies that the first year of employment may occur before the last year spent by an individual in formal education.

step, I retain highly educated workers, defined as workers who obtain a bachelor degree by age 25. In describing the characteristics of workers in the sample, I focus on the entire time span in which workers are observed. In order to perform the structural estimation of the job search model, I construct a 64-month sample including the first five years of labor market experience only. The final sample includes 311 male workers and 403 female workers, each observed for at least five years since labor market entry.[10]

It is worth noting that the selection of workers who are both highly educated and strongly labor market attached causes the sample to be unbalanced in such a way that female workers represent 56.4% of the entire sample. The unbalance between men and women strongly driven by the under-representation of young males among the most recent cohorts of college graduates (Goldin, Katz & Kuziemko 2006). As a matter of fact, among the full sample of NLSY97 individuals who obtain a bachelor degree by Round 17, 42% are males, and approximately 58% are females. The unbalance between men and women is only tenuously reduced in my sample due the selection of strongly labor market attached individuals. The similar gender composition of my sample relative to the overall sample of NLSY97 college graduates, suggests that selecting workers on the grounds of their labor market attachment does not disproportionately exclude women relative to men. In other words, the strongly labor market attached workers in my sample tend to be representative of the sex-composition of Millennial college graduates as a whole.

3.2 Sample Characteristics of Young Men and Women

Tables 1 and 2 report the average characteristics of the male and female workers in the final sample and results of t-tests for differences in means. Table 1, specifically, focuses on the time-invariant characteristics of workers and of their early-careers, measured at labor market entry. It reports information on education, fertility, family-formation decisions and early-career job changes. Table 2 reports workers' hourly wage, hours and weeks worked in the first week in employment in the first (panel (a)), fifth (panel (b)) and last (panel (c)) years in the sample, together with the characteristics of employers that employees work for, measured in the same weeks and years. The tables show that differences exist between male and female workers in both time-invariant and time-varying characteristics.

Regarding education, table 1 shows that, while all workers in the sample obtain their college degree by age 25 by construction, women are approximately 10% more likely than men to have obtained their college degree by the time of labor market entry and about 43% more likely than male workers to obtain a master's degree by age 26.

The table also shows that women tend to anticipate family-formation decisions relative to men. While approximately 70% of workers of both sexes marry by 2015, 39% of women and 26%

[10] Appendix Section A explains the construction of the final sample in more detail.

of men are either married or cohabiting by labor market entry, and 72% of women (65% of men) are either married or cohabiting by the fifth year of labor market experience. Women (59%) are also significantly more likely than men (52%) to become parent by 2015. However, only 6% of women are mothers at labor market entry, while 76% of women in the sample do not have a child by the 5th year in the labor market. Both male and female workers who have a child are about 28 years old on average at first childbirth, occurring approximately four years after labor market entry. It is worth noting that the timing of childbirth for the average worker in the sample corresponds with the moment when significant differences in labor market attachment arise between male and female workers. While it is well-known that gender differences in pay dramatically expand after childbirth (Angelov, Johansson & Lindahl 2016), in Section 3, I show that a gender pay differential arises earlier.

Table 1: Time-Invariant Sample Characteristics

	Males	Females	Diff.	Obs.
Age at labor market entry	24.25	24.32	-0.07	714
No more in education by labor market entry	0.67	0.62	0.05	714
Enrolled in school at labor market entry	0.15	0.17	-0.02	714
Bachelor degree by labor market entry	0.71	0.78	-0.07**	714
Master degree by age 26	0.07	0.10	-0.03*	714
Prospective PhD graduate	0.02	0.02	0.01	714
Married/cohabiting by labor market entry	0.26	0.39	-0.13***	714
Married/cohabiting by 3rd yr in labor market	0.48	0.60	-0.12***	714
Married/cohabiting by 5th yr in labor market	0.65	0.72	-0.07**	714
Married by 2015	0.68	0.70	-0.02	714
Has child by labor market entry	0.03	0.06	-0.03*	714
Has child by 3rd yr in labor market	0.11	0.12	-0.02	714
Has child by 5th yr in labor market	0.21	0.24	-0.03	714
Has child by 2015	0.52	0.59	-0.06*	714
Age at first child birth	28.50	28.09	0.41	400
Total number of jobs held	2.47	2.42	0.05	714
Changes employer by 5th year in labor market	0.52	0.51	0.01	714
Year of experience at first job change	3.90	3.72	0.18	462
Year of experience at first job change|changes by 5th year	3.01	2.94	0.07	366
Total number of years in sample	8.68	8.44	0.23*	714
Total number of weeks in sample	424.41	405.84	18.57***	714

Notes: NLSY97. The statistics are computed on a sample of 311 male and 403 female non African-American and non Hispanic workers. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Appendix table 15 reports the time-invariant sample characteristics for 984 workers of all races and ethnicities. Appendix table 17 reports the time-invariant sample characteristics for the subsample of 553 workers who do not have children by the fifth year on the labor market. Appendix table 18 reports the time-invariant sample characteristics for the subsample of 314 workers who do not have children by the last available NLSY97 wave, in 2015. Appendix table 19 reports the time-invariant sample characteristics for the subsample of 220 workers who do not marry by 2015.

In line with existing literature, table 2 hints that the pay gap arises and expands as male and female workers' hourly wages rise at different rates in years of labor market experience (Amato-

Patiño, Baron & Xiao 2020, Barth, Olivetti & Kerr 2021, Loprest 1992, Manning & Swaffield 2009). In particular, female workers earn as much as male workers at labor market entry (a \$16 hourly salary, panel (a)). By the last year in the sample, however, women's average wage reaches approximately \$23 per hour, a significantly lower amount relative to men's \$27 hourly pay (panel (c)). As panel (b) shows, a difference in average wages across genders arises by the fifth year of labor market experience.

The table further shows that, while at labor market entry male and female employees work as many hours per week and as many weeks per year (panel (a)), by the last year in the sample women's average weekly hours of work decrease while men's average weekly work hours rise (panel (c)). Such differences are likely to contribute to the gender gap in pay, as premia for long hours and work continuity do impact wages, predominantly among career-oriented workers in certain professional occupations (Bertrand, Goldin & Katz 2010, Gicheva 2013, Goldin 2006), where college graduates represent the vast majority of the employed workforce. Still, the increasing difference hours worked between male and female workers is unlikely to fully account for the rising gender gap in hourly pay. Appendix tables 23 and 24 show that a pay gap arises and expands over time in the labor market even among, respectively, men and women who do not have children by 2015, and men and women who do not marry by 2015, in spite of blurred gender differences in weekly work hours within these groups.

Table 2, instead, suggests that search dynamics may matter in determining both wage growth within genders and rising gender-differences in hourly pay. 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. At labor market entry, female workers are also more likely than male workers to work for employers offering other non-wage benefits such as medical and life insurance. Differences by gender in the provision of these amenities, however, disappear later on, as the share of male workers employed by amenity-providing employers tends to grow faster over time in the labor market than the share of female workers in jobs providing benefits.

The evidence that, among both men and women, wages and the share of employees working in amenities-providing jobs rises over time in the labor market is consistent with the main implications of models of hedonic job search, where workers' progressively escalate the job ladder and, by doing so, they end up working for more productive employers, the latter being more likely than less productive employers to offer both higher wages and better sets of amenities and working conditions (Hwang, Mortensen & Reed 1998). At the same time, the evidence that men's wages and the share of male workers employed in amenities-providing jobs rise faster suggests that male workers may find it easier to climb the job ladder. That is, they may be more likely than women to receive lucrative job offers from productive firms that offer benefits.

Table 2: Time-Varying Sample Characteristics by Years in Labor Market

	Males	Females	Diff.	Obs.
	(a) First Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	15.94	16.15	-0.21	714
Employer j provides unpaid parental leave	0.22	0.31	-0.10***	714
Employer j provides paid parental leave	0.32	0.49	-0.17***	714
Employer j provides child care	0.07	0.10	-0.03	714
Employer j provides flexible schedule	0.40	0.39	0.01	714
Employer j provides medical insurance	0.76	0.84	-0.08***	714
Employer j provides life insurance	0.57	0.64	-0.07*	714
Employer j provides dental care	0.69	0.77	-0.07**	714
Employer j provides stock ownership	0.21	0.19	0.03	714
Employer j number of employees	768.49	641.91	126.59	505
Average weekly hours worked at j	43.56	42.62	0.94	714
Total number of weeks employed in t	47.67	48.87	-1.20**	714
	(b) Fifth Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	21.40	20.02	1.39	714
Employer j provides unpaid parental leave	0.38	0.59	-0.21***	714
Employer j provides paid parental leave	0.48	0.57	-0.09**	714
Employer j provides child care	0.08	0.12	-0.04*	714
Employer j provides flexible schedule	0.49	0.44	0.05	714
Employer j provides medical insurance	0.91	0.92	-0.01	714
Employer j provides life insurance	0.75	0.81	-0.06*	714
Employer j provides dental care	0.85	0.87	-0.03	714
Employer j provides stock ownership	0.25	0.22	0.03	714
Employer j number of employees	824.98	726.39	98.58	623
Average weekly hours worked at j	44.38	42.03	2.34***	714
Total number of weeks employed in t	49.57	47.15	2.42***	714
	(c) Last Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	27.72	23.65	4.06***	714
Employer j provides unpaid parental leave	0.51	0.66	-0.15***	714
Employer j provides paid parental leave	0.48	0.55	-0.07*	714
Employer j provides child care	0.10	0.12	-0.01	714
Employer j provides flexible schedule	0.54	0.45	0.09**	714
Employer j provides medical insurance	0.93	0.90	0.03	714
Employer j provides life insurance	0.77	0.78	-0.02	714
Employer j provides dental care	0.82	0.84	-0.02	714
Employer j provides stock ownership	0.24	0.19	0.05*	714
Employer j number of employees	1123.62	571.77	551.85*	519
Average weekly hours worked at j	44.29	40.86	3.43***	714
Total number of weeks employed in t	41.79	37.97	3.82***	714

Notes: NLSY97. The statistics are computed on a sample of 311 male and 403 female non African-American and non Hispanic workers. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Wages and hours information for all 714 workers in the sample is available for the first five-to-ten years since labor market entry. 86 male workers and 123 female workers in the sample have missing information regarding their first employer dimension, measured as number of employees. 31 male workers and 60 female workers have missing information regarding their fifth-year employer dimension. 78 male workers and 117 female workers have missing information regarding the dimension of their last employer. Appendix tables 16 and 21 report the time-invariant and time-varying sample characteristics for the subsample of 484 workers with non-missing information for all the variables in table 2. Appendix table 20 reports the time-invariant sample characteristics for 984 highly educated workers of all races and ethnicities. Appendix table 22 reports the time-varying sample characteristics for the subsample of 553 workers who do not have children by the fifth year on the labor market. Appendix table 23 reports the time-varying sample characteristics for the subsample of 314 workers who do not have children by the last available NLSY97 wave, in 2015. Appendix table 24 reports the time-invariant sample characteristics for the subsample of 220 workers who do not marry by 2015.

This intuition is supported by the changing dimension of firms that employ workers. Interestingly, by the last year in the sample, women end up working for employers whose dimension, measured by the number of employees of the last known employer, is significantly smaller than the dimension of employers where men work, in spite of a similarity in employer dimension at labor market entry. Given the positive relation between employers' dimension, wage and amenities offered, and employees' utility predicted by job search models *à la* Hwang, Mortensen & Reed (1998), the evidence above suggests that female workers may be subject to stronger search frictions relative to men, be more likely to experience constrained job changes, and receive job offers entailing lower wages than men conditional on the provision of amenities. All these factors would entrench female workers' ability to climb the job ladder and contribute to the pay gap between male and female workers. Yet, it is not possible to exclude that, as women change jobs, they willingly forgo wage improvements in exchange for the provision of valuable amenities. That is, it is not possible to exclude that women's unobserved preferences for benefits such as flexibility and parental leave may impact the rising gender wage gap. All these considerations remain valid when the subsample of 484 male and female workers with non-missing information on employer's dimension are analyzed, as tables 16 and 21 in the Appendix show.

Three final points are worth mentioning. First, the early careers of both male and female workers in my sample are highly dynamic. As table 1 shows, 462 workers (65% of the sample) change at least one job throughout their early careers, and 74% of these workers change their first job around the third year of labor market experience. In particular, 52% of women (and 51% of men) in the sample change their first job by the fifth year in the labor market. Specifically, they enter their second job during the third year in the labor market. This shows that both young men and women do actively shop for jobs at labor market entry, thus reducing concerns that the changes in amenities and wages reported in 2 solely captures changes in contractual benefits within-firms.

Second, the early-career dynamics experienced by the average man and woman in my sample are not driven by the differential behavior of workers who either become parents or marry. As Appendix tables 18 and 19 respectively show, 66% of workers who do not become parents by 2015 and 65% of workers who do not marry by 2015 change at least one job throughout their early career. In addition, 52% of women who do not have children and 53% of women who do not marry by 2015 change at least one job by the fifth year of labor market experience. As the average worker in my sample, women who do not marry and do not have children also enter their second job during the third year of labor market experience.

Finally, the evidence in tables 23 and 24 in the Appendix shows that, among men and women who do not have children or do not marry by 2015, wages, employer-specific characteristics and the gender pay gap evolve similarly as they do for the entire sample. This evidence supports my choice to model men and women as independent agents in the labor market, rather than modeling household joint-search dynamics.[11]

3.3 Labor Market Transitions and Labor Market Attachment by Gender

Tables 3 to 5 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 in 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 3: Frequencies of Employment Statuses

	Males	Females	Diff.	Std. Error	Obs.
	(a) First Five Years in the Labor Market				
Job-to-Job transition	0.487	0.391	0.096***	0.031	1040
Gap in weeks between two consecutive jobs	4.914	5.116	-0.202	0.609	1040
Gap in weeks between jobs conditional on Gap > 0	9.577	8.405	1.172	0.985	593
Employed	0.809	0.790	0.019*	0.011	5635
Unemployed	0.060	0.056	0.004	0.006	5635
Out of Labor Force	0.119	0.144	-0.024***	0.009	5635
Employed but not working	0.000	0.001	-0.001	0.000	5635
Other, not working	0.011	0.010	0.001	0.003	5635
	(b) After Fifth Year in the Labor Market				
Job-to-Job transition	0.438	0.372	0.065	0.045	517
Gap in weeks between two consecutive jobs	6.604	8.148	-1.544	1.403	517
Gap in weeks between jobs conditional on Gap > 0	11.741	12.980	-1.240	2.196	312
Employed	0.656	0.612	0.044***	0.014	4699
Unemployed	0.033	0.025	0.007	0.005	4699
Out of Labor Force	0.062	0.120	-0.058***	0.008	4699
Employed but not working	0.000	0.000	0.000	0.000	4699
Other, not working	0.249	0.242	0.006	0.013	4699

Notes: NLSY97. Sample as in Table 1. In this table, one observation refers to a worker-specific labor market status spell. A labor market status spell is a group of one or more consecutive weeks such that an employee is observed in the same labor market status. If a worker is employed by two different employers in two consecutive groups of weeks, the latter account for two different labor market status spells. The sample includes 5635 worker-specific labor market status spells by the fifth year in the labor market and 4699 worker-specific labor market status spells for the following years. The share of "Job-to-Job transitions" is the share of all job changes such that a worker is employed by two different employers in two consecutive weeks. The sample includes 1557 job change episodes. Among these job changes, 905 involve a gap of at least one week between the end of the previous employment relationship and the beginning of the new employment relationship.

Table 3 characterizes employment status spells. 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

[11] Joint-search dynamics may affect both married workers' choices and constraints (Guler, Guvenen & Violante 2012) and the estimates of the characteristics of the job offers that workers receive (Flabbi & Mabli 2018). However, the similarity in individual characteristics and career paths between the average unmarried woman, the average woman without children, and the average woman in my sample tend to rule out that married women's and mothers' search behavior and preferences should radically differ from those of the typical female worker soon after labor market entry.

changes in the unique identifier of the employer where a worker is employed.[12]

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 the fifth year of experience, women are significantly less likely than men to be observed in an employment spell (61% of the time versus 66% of all spells) 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 more likely than female workers to experience job-to job transitions.

For both male and female workers, labor market attachment decreases after the fifth year in the labor market, and a gender-gap in active labor market participation emerges five years after labor market entry too. Table 4 shows that men and women spend less than two spells and, respectively, approximately 10 and 12 weeks overall out of the labor market at the very beginning of their careers, while they spend approximately 45 (men) and 57 (women) weeks out of labor later on.

Table 4: Number of Career Interruptions and Total Number of Weeks Out of Employment

	Males	Females	Diff.	Std. Error	Obs.
	(a) First Five Years in the Labor Market				
Total number of spells out of employment	1.460	1.695	-0.235	0.156	714
Total number of weeks out of employment	10.299	12.270	-1.971	1.279	714
	(b) After Fifth Year in the Labor Market				
Total number of spells out of employment	2.338	2.759	-0.422**	0.165	714
Total number of weeks out of employment	45.199	57.390	-12.190***	4.421	714

Notes: NLSY97. Sample as in Table 1. One observation the first worker-week-job in the panel. "The total number of spells out of employment" is the number of consecutive-weeks slots such that a worker is not associated with an employer during the first five-to-ten years since labor market entry. The "total number of weeks out of employment" is the overall number of weeks such that a worker is not associated with an employer during the first five-to-ten years since labor market entry.

Similar differences can also be observed in Table 5, reporting the average number of weeks spent by workers in four categories of employment status in a year. 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 two to almost three weeks between the first five years on the labor market and the consecutive years. Furthermore, both men and women are observed in a significant number of spells out of the labor force. Yet, the average number of weeks out of the labor force substantially increases for women five years after labor

[12]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 excludes the 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. The inclusion of these transitions would have caused a discrepancy between the number of non missing observations in the first and second line of panel (a), but it would have not changed the results. The latter are available upon request.

market entry, generating a non-negligible 8-weeks gap in labor force participation relative to men.

Table 5: Yearly Continuous Weeks in Employment Status

	Males	Females	Diff.	Std. Error	Obs.
	(a) First Five Years in the Labor Market				
Employed	40.279	38.846	1.432***	0.508	4498
Unemployed	7.014	7.275	-0.261	0.817	325
Out of Labor Force	6.595	6.212	0.383	0.558	751
Other, Not Working	12.111	21.176	-9.065***	3.263	61
	(b) After Fifth Year in the Labor Market				
Employed	42.560	39.699	2.861***	0.602	2965
Unemployed	9.154	11.232	-2.078	1.908	134
Out of Labor Force	7.395	15.444	-8.049***	1.326	448
Other, Not Working	24.151	25.133	-0.981	0.917	1152

Notes: NLSY97. Sample as in Table 1. One observation is a worker-specific labor market status spell. This table shows average the duration in weeks of worker-specific labor market status spells by sex. Labor market status spells are defined as in Table 3. Overall, the sample includes 5635 labor market status spells by the fifth year of labor market experience and 4699 labor market status spells in years of experience five to ten.

Three main facts emerge regarding workers' characteristics. First, male and female workers' job specific characteristics, labor market attachment and labor market outcomes evolve an diverge over time. Second, the sample I select includes male and female workers who 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 search frictions, job offers 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.

4 Descriptive Analyses

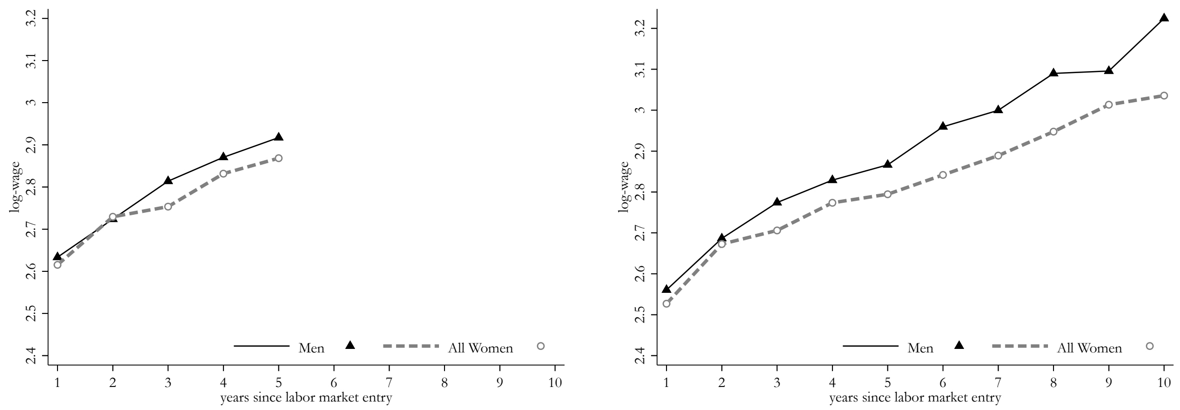
In this section I analyze the early career wage gap between the highly educated male and female workers in the NLSY97 sample. I document that unobserved job change determinants (e.g. preferences, likelihood of receiving job offers, and gender differences in the job offers that workers receive) and consequent outcomes, may rationalizing its emergence and its increase over time in the labor market, even when labor market attachment is accounted for and even when otherwise remarkably similar male and female workers are compared. As such, this section provides a battery of descriptive evidence that motivates and supports the structural model I estimate in section 5 and its results.

4.1 Experience Wage Profiles Differ By Gender

The two graphs in figure 1 report the composition adjusted mean log-wages of male and female workers by years of experience, the latter being defined in terms of time since labor market entry. The adjustments for composition weight the contribution of workers who enter the labor market in any year (cohort) by the overall contribution of their cohort to the total amount of weeks worked by all workers in the sample. The adjustments are explained in appendix section C.1. In figure figure 1, panel (a) plots the log-wage path during the first five years of experience of workers entering the labor market between 2000 and 2012. Panel (b) plots the log-wage path during the first ten years of experience of workers entering the labor market between 2000 and 2007, thus being observable for ten years.

The paths of log-wages in figure 1 show that a gender difference in log-wages arises soon after labor market entry among young highly educated workers. Specifically, 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 2. However, by the beginning of the third year in the labor market, male workers' average wage overcomes the hourly pay that female workers receive by at least 3 log-points. The gap expands until reaching a maximum of approximately 20 log-points by the beginning of the tenth year of experience.

Figure 1: Composition Adjusted Mean Log-Wages - All Workers

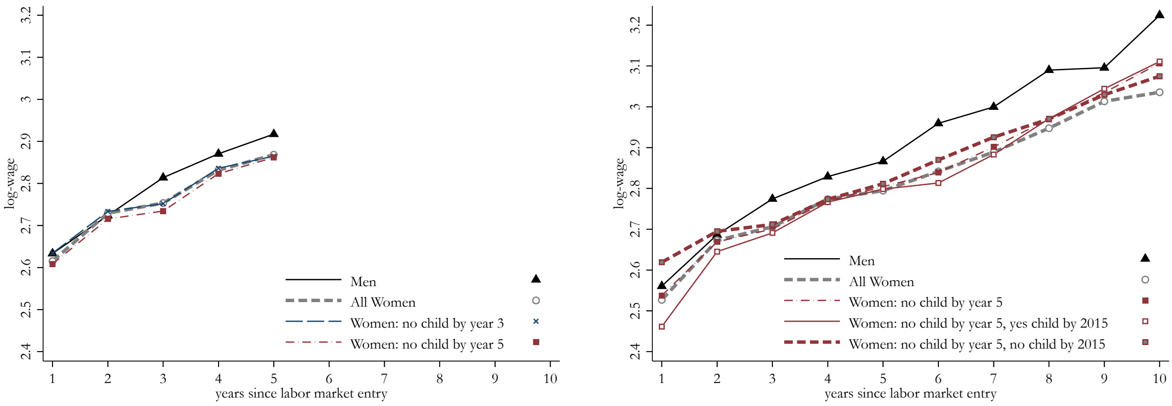


(a) Enter Labor Market in 2000-2012 (b) Enter Labor Market in 2000-2007

Notes: National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic workers who graduate from college by age 25, who are continuously in employment by the fifth year on the labor market and who enter the labor market between 2000 and 2012 (panel (a)), or between 2000 and 2007 (panel (b)). For each individual in the sample I only consider the first job in chronological order held in a certain year. The adjustment for composition is explained in Appendix Section C.1.

The wage patterns in figure 1 suggest that a gender wage differential arises between highly educated male and female workers before any difference in labor market participation occurs, and before the average worker in the sample has children. Importantly, figure 2 shows that the pay-gap does not arise as a consequence of the differential behavior of women who have children. Panel (a) in figure 2, in fact, shows that the early-career wage path of women who do not have children by the third year of experience (blue, thick dashed line) and of women who do not have children by the fifth year of experience (maroon, thin, dashed line) do not differ from the wage path of the average woman. Panel (b) further corroborates the evidence that a pay gap arises soon after labor market entry even between all men and women who do not have a child by 2015, that is, 10-to-15 years since labor market entry. For these women as well (maroon, thick, dashed line), wage growth begins to decline around the third year of experience, giving rise to a pay-gap with respect to men that persists throughout their early careers.[13]

Figure 2: Composition Adjusted Mean Log-Wages - Women By Parental Status



(a) Enter Labor Market in 2000-2012

(b) Enter Labor Market in 2000-2007

Notes: National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic workers who graduate from college by age 25, who are continuously in employment by the fifth year on the labor market and who enter the labor market between 2000 and 2012 (panel (a)), or between 2000 and 2007 (panel (b)). Appendix figure 6 shows the composition adjusted experience paths of log-wages for college graduate workers of all races and ethnicities, and for women of all races and ethnicities by parental status.

4.2 Returns to Experience: Search Capital, General Human Capital and Labor Market Attachment

In the previous section, I showed that the average wages that highly educated men and women earn, increasingly diverge over years of labor market experience. In what follows, I study gender-specific returns to experience to provide evidence that job changes determine a non negligible portion of the early career gender wage gap. 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 workers' 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

[13] Appendix figure 6 provides evidence that these results are unaffected when comparing highly-educated men and women of all races and ethnicities. However, among all workers the gender pay gap is smaller, mostly as a result of the lower wages that non-white men tend to obtain relative to white men, which flatten the average man's experience wage profile.

exceeds the present value of their current state. General human capital refers to the set of skills that workers acquire on the job and are transferable across jobs, reflecting into wage increases as workers spend more time in the labor market. 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).

If returns to experience are mostly linked to general human capital, then the gender pay gap should arise in early careers if women do not participate assiduously to the labor market, if they work significantly less than men, or if women's general human capital is *priced* less than men's. If search capital matters in determining workers' wages, their growth should be linked to workers' wage gains following job changes, conditional on workers' actual experience neat of career interruptions. If so, wages may grow at different rates by gender if women face fewer chances of receiving utility enhancing job offers (search frictions), if the offers they receive are not as lucrative as men's (job offers), or if they willingly forgo some wage gains in order to work for employers providing amenities such as flexibility or parental leave (preferences).

Here, I first show that gender differences in returns to experience are not driven by different levels of labor market attachment between male and female workers. Then, I study the contribution of returns to *search capital* to the early career gender pay gap. In particular, I show that gender differences in returns to job changes (proxying *search capital*) determine a non-negligible part of the early career pay gap, controlling for a number of measures proxying for *general human capital*. Finally, I provide evidence that voluntary job changes bring wage gains for men but not for women. It suggests that male workers are more successful than female workers in climbing the job ladder, even as workers of different sexes fall off the ladder (i.e. exit employment, exit the labor market, or lose jobs) at similar rates.

4.2.1 Disentangling Returns to *Human* and *Search* Capital from Returns to 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 attachment. Following Light & Ureta (1995) I estimate 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.[14] 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.

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

[14]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.

Where $J = 1, ..., 10$ is the year of potential experience for a worker observed in calendar year t. The third measure of experience, that I name *work history* as Light & 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 can be written as

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

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 an error term. The work history model can be written as

$$w_{it} = \alpha + \sum_{\iota=1}^{I} \beta_\iota \text{exp}_{i,\iota t} + x_{it}'\delta + \varepsilon_{it} \quad (2)$$

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.

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. The *actual experience* and the *work history* models also control for the number of career interruptions (spells out of employment). All models are estimated separately for men and women through fixed-effect estimator.[15]

In Table 6, 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 in the labor market.[16]

The measures of experience listed above capture different aspects of workers' behavior in the labor market. *Potential experience* can be interpreted as a raw measure of general human capital, search capital and labor market attachment. As the wage-ratios in table 6 (col. (3) and (6)) show, returns to experience appear to be higher for young, highly educated male workers relative to their female counterparts. Still, part of this difference may be driven by the longer career interruptions that some women experience during the first ten years in the labor market,

[15] 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. Results are available upon request.

[16] Appendix Table 25 reports the coefficient estimates from the different models. Appendix Table 26 reports the model-specific predicted log-wages and the standard errors of the predictions separately for male and female workers. The predictions are computed for workers with one year of tenure, living in a MSA and not in the Southern region of the United States, and working between 41 and 50 hours per week in the second, fourth and sixth year in the labor market.

and that are not controlled for in the potential experience model. 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 I estimate models using measures of labor market experience that clean out periods spent out of work and control for career interruptions. The results of 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.

Table 6: Gains from Experience

	Males			Females		
	Work Hist.	Actual Exper.	Potential Exper.	Work His.	Actual Exper.	Potential Exper.
	(1)	(2)	(3)	(4)	(5)	(6)
	One Year of Tenure			One Year of Tenure		
Experience 2	1.05	1.04	1.00	1.07	1.04	1.00
Experience 4	1.25	1.24	1.18	1.25	1.23	1.16
Experience 6	1.50	1.48	1.39	1.40	1.42	1.33

Notes: 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 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.

4.2.2 The Contribution of *Search* Capital to the Gender Wage Gap

The evidence above suggests that returns to actual experience are higher for men than for women, but *actual experience* can be thought of as a measure of general human capital and search capital neat of labor market attachment. In the next step, I use an Oaxaca-Blinder decomposition to understand the contribution of *search capital* to the early career wage differential between young highly educated men and women. In order to do so, I estimate the actual experience model (1) through fixed-effect estimator separately on male and female workers, controlling for the number of times a worker changed job by year t, years of tenure at current employer and tenure squared, a dummy capturing whether a worker has obtained his/her bachelor degree by year t, the size of current employer j measured by the logarithm of number of employees working at j in time t, the number of times (i.e. spells lasting at least one week) a worker exited the labor force by t and hours worked in year t.[17]

Since the models I estimate condition upon a series of proxies for *general human capital* (quadratic term in actual experience, number of spells out of employment, current work hours),

[17] I do not control for occupation and industry categories and, 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 interpret the explanatory variable capturing the number of job changes by year t as a measure of workers' *search capital*.

I decompose the predicted gender wage gap between male and female workers, using the wage what women would have obtained if their productivity related characteristics where priced according to male workers' wage structure (Fortin, Lemieux & Firpo 2011) as a counterfactual. That is, letting f_i be an indicator variable for female workers, I decompose the gender log-wage differential as

$$\hat{E}[w_{it}|f_i = 0] - \hat{E}[w_{it}|f_i = 1] = \sum_{k=1}^{K} \bar{x}_{kf} \left(\hat{\beta}_m - \hat{\beta}_f\right) + \sum_{k=1}^{K} \hat{\beta}_{mk} \left(\bar{x}_{km} - \bar{x}_{kf}\right) \tag{3}$$

The left hand side of equation (3) is the difference in the 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 return to 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).[18] The second part on the right-hand side 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.

The first panel on the left in figure 3 reports selected results of the decomposition for all workers in the sample. In particular, it shows that highly educated and labor market attached male workers earn, on average, 9.9 log-points more per hour during the first ten years in the labor market relative to their female counterparts. The figure also shows that virtually the entire gap is explained by the wage structure, that is, by the higher returns to productivity-related characteristics earned by male workers relative to female workers. Differences in characteristics, instead, do not explain the pay gap, consistently with the strong similarities in labor market attachment and behavior between the male and female workers in my sample. The third column in figure 3, panel (1), shows that gender differences in returns to job changes alone determine a pay-gap of about 7.1 log-points, explaining 72% of the raw wage gap between male and female workers. Appendix table 27 panel (a) shows the full set of results from the decomposition.

Panel (2) in figure 3 shows the results of the decomposition performed for employees in executive and professional careers.[19] This exercise is relevant, since its results rule out that the contribution of returns to job changes to the gender pay gap is entirely due to gender differences in workers' selection into careers offering different opportunities to obtain lucrative job offers and

[18] The unexplained gap cannot be identified in panel data using fixed effect estimator. I report its estimated value in Appendix table 27 for completeness.

[19] In panel (2) a worker is defined to be in executive or professional career if they report to be employed in executive, managerial, management related or professional 1-digit Census occupations the majority of times they are observed in the panel.

escalate the job ladder. For workers in executive and professional careers, returns to productive characteristics explain 94% of the 8 log-point early career pay gap between male and female workers, and the higher returns to job changes enjoyed by male workers explain alone 67% of the gap.

Figure 3: Wage Gap Decomposition - Selected Workers Categories

Notes: National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic workers who are continuously in employment by the fifth year on the labor market and who enter the labor market between 2000 and 2011. The sample only includes individuals who obtain a college degree by age 25 and never leave the labor market for more than one year in any of the first five years in the labor market. For each individual in the sample I only consider the first job in chronological order held in a certain year. Panel (1) shows the wage gap among all workers in the sample, panel (2) shows the gap among workers who are mostly observed in Executive, Managerial and Professional specialty occupations. For each group, the first bar on the left (dark) shows the raw (log) wage gap between male and female workers, the second bar represents the wage gap due to different returns to observed characteristics, and the bar on the right shows the wage gap due to different returns to job changes. Appendix table 27 shows the complete set of results of the wage gap decomposition. Appendix figure 7 shows that the results of the decomposition are unaffected when using the predicted wage that a worker with the average male's characteristics would obtain given women's returns to observed characteristics as a counterfactual.

The findings reported in this section support the idea that, when observationally similar workers are compared, search dynamics matter in explaining residual differences in labor market outcomes between male and female workers. In particular, since male and female workers appear to change jobs at similar rates, the results suggest that male workers may draw job offers from a wage distribution that first-order stochastically dominates the distribution of wages offered to female 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 valuable amenities such as flexibility or parental leave.

4.2.3 Gender Differences in Gains from Job Changes: Differences in Returns to Search Capital

In the previous section, I showed that a non-negligible portion of the early career gender gap in pay gap among college graduate workers can be explained by gender differences in returns to job changes. I now estimate the average wage gains and losses from job changes by gender. In order to do so, I estimate a regression model of the form

$$
\begin{aligned}
w_{it} = \alpha + \beta_1 \text{exp}_{i,t-1} + \beta_2 \text{exp}^2_{1,t-1} + \delta \text{change\_job}_{i,t-1} + \\
+ \gamma \text{change\_job}_{i,t-1} * \text{exp}_{i,t-1} + \eta \text{change\_job}_{i,t-1} * \text{exp}^2_{i,t-1} + x'_{i,t-2}\psi + \varepsilon_{i,t}
\end{aligned} \tag{4}
$$

Where $\text{exp}_{i,t-1}$ is the amount of actual experience accumulated by workers until $t-1$, and change_job is an indicator variable taking value 1 for workers who changed job between $t-2$ and $t-1$. $x^{'}_{i,t-2}$ is a vector of worker and job-specific characteristics at $t-2$, while $\varepsilon_{it} = \nu_i + u_{it}$ where ν_i is an individual specific fixed effect and u_{it} is an error term.

The regressors in model (4) are lagged because, while mobility decisions can be motivated by a wage offer superior to the wage received at one's current job, at the beginning of their careers 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).

Since job changes occur (if any) between $t-2$ and $t-1$, controls for pre-existing characteristics refer to $t-2$. They include two dummy variables indicating whether a worker was enrolled in school or college at $t-2$, whether the worker obtained their 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 leave 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 model allows to compare the wage growth experienced by workers who change job (parameters $\beta_1 + \beta_2 + \gamma + \eta$), relative to the wage growth experienced by job stayers (parameters $\beta_1 + \beta_2$), conditional on differences in wage levels across groups and on previous labor market histories.

On top of the specification described above, I also allow the parameters γ and η to take different values depending on the reason determining a job change. As a matter of fact, workers change jobs for different reasons, and part of the contribution of returns to search capital to the gender pay gap is likely to include gender differences along this dimension.

Table 7 shows that about 38% of both male and female workers' job changes are driven by workers' willingness to take another job or look for another job (i.e. job shopping). Hence, only a third of job changes in the data can be neatly rationalized through the lens of a search model and, abstracting from preferences for amenities, should lead to wage gains as workers' climb the job ladder. In addition, table 7 shows that gender differences exist in job changes motives. Specifically, while women change job due to family related reasons or pregnancy only 4.3% of the times, the difference relative to men changing job due to family obligations (1%) is striking. Also, transportation and mobility constraints motivate 11.2% of female workers' job changes, but only 7% of men' s job changes. Finally, 5% 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 3.8%.

Table 7: Reasons Determining Workers Leaving Their Previous Job

	Why Job Ended?				
	Males	Females	Diff.	Std. Error	Obs.
Layoff	0.062	0.043	0.019	0.015	972
Plant closes	0.031	0.009	0.022**	0.009	972
Fired	0.024	0.022	0.002	0.010	972
End project	0.065	0.047	0.018	0.015	972
Pregnancy or family	0.010	0.043	-0.034***	0.010	972
Look for other job	0.041	0.036	0.005	0.013	972
Take other job	0.336	0.339	-0.003	0.031	972
School	0.048	0.043	0.005	0.014	972
Transportation	0.070	0.112	-0.042**	0.018	972
Other legal or medical	0.024	0.022	0.002	0.010	972
Dislikes working conditions	0.038	0.050	-0.012	0.013	972
Other	0.007	0.011	-0.004	0.006	972
Other unknown	0.245	0.223	0.021	0.028	972

Notes: 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. The sample includes 1085 job separation episodes. The table reports the shares of separations due to different motives.

The evidence in Table 7 shows that, overall, female workers may face stronger constraints to their mobility across jobs relative to male workers. In spite of a similar share of "job shoppers" among male and female workers, the higher share of women changing jobs for family-related reasons or due to limited ability to commute, suggests that the range of options women draw job offers from may be more limited than the range of options available to men. If so, first, the same constraints determining women's moves may as well impact their preferences for amenities that improve work-life balance, such as schedule flexibility and parental leave. Second, such constraints may make women's labor supply more rigid at the firm level, that is, less responsive to wage changes. In this circumstance, employers end up having a monopsonistic power (Manning 2003) enabling them to set lower wages for female workers relative to the wages they would offer to a comparable man. This would happen in jobs that do not provide amenities as well as in jobs that do provide amenities, irrespective of workers' preferences. If this happens, then not only women who undertake constrained transitions across jobs should lose more than men, but also women who willingly change jobs in order to improve their labor market prospects should gain less than men from job changes. To account for heterogeneity in job change motives, I estimate the following regression

$$
\begin{aligned}
w_{it} = \alpha + \beta_1 \text{exp}_{i,t-1} + \beta_2 \text{exp}^2_{1,t-1} + \sum_{k=1}^{K} \delta_k \text{change\_job\_reason}_{k,i,t-1} + \\
+ \sum_{k=1}^{K} \gamma_k \text{change\_job\_reason}_{k,i,t-1} * \text{exp}_{i,t-1} + \\
+ \sum_{k=1}^{K} \eta_k \text{change\_job\_reason}_{k,i,t-1} * \text{exp}^2_{i,t-1} + x'_{i,t-2}\psi + \varepsilon_{i,t} \qquad (5)
\end{aligned}
$$

Where $\text{change\_job\_reason}_{k,i,t-1}$ is 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 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); *dislikes job* (worker unsatisfied with pay, working conditions, relationships with colleagues and/or supervisor at their last job); *mobility constraints* (personal mobility constraints or lack of appropriate transportation infrastructures); *other* (legal or medical problems, school enrollment and other unknown reasons). $\varepsilon_{it} = \nu_i + u_{it}$ where ν_i is an individual specific fixed effect and u_{it} is an error term.

The regression compares the wage growth experienced by workers who change job for a specific reason (parameters $\beta_1 + \beta_2 + \gamma_k + \eta_k$), relative to the wage growth experienced by job stayers (parameters $\beta_1 + \beta_2$), conditional on differences in wage levels across groups and on previous labor market histories. Controlling for the reasons determining job changes allows to reduce concerns that gender-differences in returns from job changes is strongly affected by gender-differences in workers' self-selection into the decision to switch job.

Table 8 shows the coefficients of interest from regression 4 (columns (1) and (2)) and from regression 5 (columns (3) and (4)), estimated through fixed effect estimator and cluster standard errors at the worker level. The interaction coefficients in columns columns (3) and (4) refer to workers who left their previous job in order to look for or accept another job offer (job *shoppers*). These workers are arguably the ones whose job-change decisions are the most consistent with job search models.

The results in table 8 hint that male workers who change jobs experience significant wage-level losses that are promptly compensated by an economically and statistically significant gain in terms of wage growth rate. Female workers who change jobs, instead do not appear to experience any significant wage-level or wage-growth gain. Interestingly, the coefficients capturing job changers' gains in returns to experience (fourth row in the table) are higher for both men and women when *job shoppers* only are compared to job stayers. It suggests that these workers, and predominantly men, do take future wage prospects into account when switching job.

Table 8: Returns to Job Change - Selected Coefficients

	Compare All Job Changers with Job Stayers		Compare Job Shoppers with Job Stayers	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
	b/se	b/se	b/se	b/se
Actual Experience=AE at (t-1)	0.0767**	0.0808	0.0771**	0.0759
	(0.0378)	(0.0574)	(0.0372)	(0.0586)
AE(t-1) Squared	0.0008	-0.0025	0.0010	-0.0021
	(0.0036)	(0.0059)	(0.0036)	(0.0060)
Change Job in t-1(**I**[Change(t-1)])	-0.2575	-0.0056	-0.2597*	-0.0245
	(0.1703)	(0.0895)	(0.1468)	(0.1252)
AE(t-1)***I**[Change(t-1)]	0.1375	0.0572	0.1739**	0.0662
	(0.0866)	(0.0482)	(0.0837)	(0.0605)
AE(t-1)Sqr***I**[Change(t-1)]	-0.0108	-0.0078	-0.0160	-0.0079
	(0.0099)	(0.0060)	(0.0106)	(0.0081)
Adjusted R^2	0.123	0.107	0.135	0.107
N	1790	2188	1790	2188
Reason Driving Job Change	N	N	Y	Y
Controls	Y	Y	Y	Y
Time Dummy	N	N	N	N
Time Trend	N	N	N	N
Occupation $t-2$	Y	Y	Y	Y
Industry $t-2$	Y	Y	Y	Y
Additional Contr. $t-2$	Y	Y	Y	Y

Notes: 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. All models 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 $t-2$ employer, 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 $t-2$. All models also include 1-digit occupation and 1-digit industry dummies, and controls for whether $t-2$ employer offered respectively, medical insurance, life insurance, dental care, a retirement plan, and stock ownership to employees. The table shows the coefficients of the experience polynomial and of its interactions with the job-change dummies. Appendix table 28 reports the full-set of models (1) and (2) estimated coefficients in different specifications. Appendix table 29 reports the full-set of models (3) and (4) estimated coefficients in different specifications.

Using the estimated coefficients in columns (3) and (4), it is possible to show that the average male job changer, who switches his first job between years 2 and 3 in the labor market, experiences a 22% wage growth one year later. The average female worker, changing her first job similarly early, experiences a 18% wage growth between the third and fourth year in the labor market. Comparing the average man and woman beginning their careers with, respectively, a \$15.94 wage and a \$16.15 wage, the results from regression 5 imply a pay gap of \$0.81 per hour in the fourth year of experience. This amounts to approximately 60% of the hourly pay gap observed during the fifth year of experience.[20] Although the shares of men and women who leave their employer to accept another job are remarkably similar in the data, young female workers do not seem to experience as high wage gain associated with job shopping and job ladder climbing as young men do.

As a robustness check, I further expand the regression model 5 to estimate returns to job changes by comparing job shoppers and job stayers who are equal in terms of their family formation decisions, conditional on their work history, and controlling for any other reason driving job changes. In the first two specifications, reported in panel (a) of table 9, I assume that, after either getting married (panel (a1)) or having children (panel (a2)), workers may choose their jobs and careers differently than they previously would. Hence, I estimate returns to job changes by comparing the time t wage of job changers who had not made a family-formation decision by the time they decided to change job, $(t-2)$, and job stayers with the same characteristics. I observe that, for unmarried workers and for workers without children by the time they decided to change job, returns to job changes are not different from their value for the average man and woman in my data. In the regression models whose results are reported in panels (b1) and (b2), I assume that workers who get married or have a child by t might have anticipated these decisions earlier on, thus making these workers potentially different from the average worker in my sample in terms of career and job-change decisions. Yet, the estimates of returns to job changes for these workers too are quantitatively and qualitatively similar to the results I obtain for the full sample. Finally, returns from job changes remain unaffected when comparing for men and women who do not marry (panel (b3)) and who do not have children (panel(b4)) by 2015. Interestingly, returns from job changes remain statistically significant for men who do not marry and who do not have children by selected years, in spite of the small number of observations for workers in these groups.

To give a sense of these results, men who do not have children by 2015 experience a 21% wage gain, approximately, between the third and fourth year of experience, if they changed job in the previous year. For women without children by 2015, the wage gain in the same time span following a similar job-shopping move amounts to 9.5%.

[20]In order to perform these quantifications, I use the average year of experience at first job change reported in table 1, and the average wage by year of experience reported in table 2 panels (a) and (b).

Table 9: Returns to Job Change - Selected Coefficients for Not Married Workers and Workers Without Children

	(a) Postdated JC Decision				(b) Anticipated JC Decision							
	No Married by $(t-2)$ (a1)		No Child by $(t-2)$ (a2)		No Married by t (b1)		No Child by t (b2)		No Married by 2015 (b3)		No Child by 2015 (b4)	
	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Actual Experience=AE at (t-1)	0.0614*	0.0834	0.0769*	0.0698	0.0685*	0.0754	0.0644*	0.0760	0.0690*	0.0823	0.0641*	0.0699
	(0.0369)	(0.0585)	(0.0402)	(0.0590)	(0.0378)	(0.0615)	(0.0384)	(0.0582)	(0.0383)	(0.0628)	(0.0378)	(0.0593)
AE(t-1) Squared	0.0025	-0.0032	0.0014	-0.0011	0.0017	-0.0020	0.0027	-0.0019	0.0009	-0.0021	0.0018	-0.0011
	(0.0037)	(0.0060)	(0.0043)	(0.0059)	(0.0037)	(0.0062)	(0.0039)	(0.0059)	(0.0037)	(0.0062)	(0.0037)	(0.0059)
Change Job in t-1(**I**[Change(t-1)])	-0.2732	-0.0875	-0.2883*	-0.0594	-0.3329	-0.0791	-0.3019*	-0.0532	-0.5420	-0.2153	-0.3077	-0.0777
	(0.1714)	(0.1613)	(0.1549)	(0.1381)	(0.2114)	(0.2002)	(0.1648)	(0.1482)	(0.3856)	(0.3425)	(0.3000)	(0.2523)
AE(t-1)*I[Change(t-1)]	0.2077**	0.0961	0.2105**	0.0846	0.2369**	0.0594	0.2285**	0.0862	0.3297*	0.0859	0.1970	-0.0310
	(0.0939)	(0.0903)	(0.0888)	(0.0673)	(0.1145)	(0.1067)	(0.0980)	(0.0709)	(0.1826)	(0.1557)	(0.1498)	(0.1043)
AE(t-1)Sqr*I[Change(t-1)]	-0.0204*	-0.0143	-0.0232**	-0.0101	-0.0229*	-0.0092	-0.0266**	-0.0122	-0.0320*	-0.0107	-0.0184	0.0058
	(0.0105)	(0.0146)	(0.0112)	(0.0092)	(0.0126)	(0.0167)	(0.0132)	(0.0104)	(0.0192)	(0.0235)	(0.0163)	(0.0138)
Adjusted R^2	0.165	0.106	0.144	0.105	0.141	0.105	0.168	0.104	0.148	0.108	0.159	0.110
N	1790	2188	1790	2188	1790	2188	1790	2188	1790	2188	1790	2188
N_g	304	382	304	382	304	382	304	382	304	382	304	382
N Obs. No Married or No Child	1094	1205	1481	1721	881	968	1287	1442	528	602	810	839
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occupation $t-2$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry $t-2$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Additional Contr.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: 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. All models include the same control variables as in table 8 columns (3) and (4). Models (1) and (2) allow for the possibility that the decision to change jobs differs between married and unmarried workers. Hence, they include a dummy controlling for whether a worker was married in $(t-2)$ and its interactions with the experience polynomial, with the job change dummy, and with the interaction between the job change dummy and the experience polynomial. Models (3) and (4) allow for the possibility that the decision to change jobs differs between workers with and without children. They include a dummy controlling for whether a worker had a child in $(t-2)$ and its interactions with the experience polynomial, with the job change dummy, and with the interaction between the job change dummy and the experience polynomial. Models (5) and (6) include a dummy variable taking value 1 for workers who marry by year t, together with a full set of interactions. They account for the possibility that workers decisions to change job may differ between unmarried workers and workers who are either married or anticipate a forthcoming marriage occurring by year t. Following a similar logic, models (7) and (8) include a dummy variable taking value 1 for workers who have a child by year t. Models (9) and (10) and models (11) and (12) respectively, also assume that workers may be forward-looking, hence making job-change decisions differently if they anticipate getting married or having children by 2015, the last available NLSY97 round year. These models interact the experience variable, the job change dummy and their interaction with indicators taking value 1 for workers who, respectively, marry by 2015 or have a child by 2015.

4.2.4 Gender Differences in Job Change Determinants

The evidence in the previous section strongly hints that differences exist in returns to job changes, determining a large portion of the early career gender pay differential, even among equally highly educated male end female workers who are equally willing to participate to the labor market. The findings suggest that women who change jobs for career-related reasons do not gain in terms of wages. It means that female workers may face worse labor market prospects than male workers, both because they may find it harder to obtain job offers (search frictions), and because they may receive job offers that systematically entail lower wages relative to men (job offers). The evidence above, however, does not allow to exclude that women are somehow willing to forgo some wage gains due to their preferences for amenities such as flexibility and parental leave.

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 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 positively contribute to workers' utility must decrease the probability of quitting a 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:

$$
\begin{aligned}
y^*_{ijt} &= z'_{ijt}\xi + \nu_i + u_{ijt} \\
&= \alpha + \beta w_{it} + \gamma \mathbf{I}\left[\text{Parental Benefits}_{ijt}\right] + \delta \mathbf{I}\left[\text{Flexible Schedule}_{ijt}\right] + x'_{ijt}\eta + \nu_i + u_{ijt} \qquad (6)
\end{aligned}
$$

$$y_{ijt} = \mathbf{I}\left[j(t) \neq j(t+1)\right] = \mathbf{I}\left[y*_{ijt} \geq 0\right] \tag{7}$$

$$\Pr\left[y_{ijt} = 1 | z_{ijt}, \nu_i\right] = \frac{\exp\{z'_{ijt}\xi + \nu_i\}}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \tag{8}$$

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, $\mathbf{I}\,[\text{Parental Leave}_{ijt}]$ takes value 1 if employer j offers paid leave, unpaid leave or child care to i in t, $\mathbf{I}\,[\text{Flexible Schedule}_{ijt}]$ takes value 1 if flexible schedule is available for i at employer j in year t. I am interested in observing whether the probability of job changes varies differently with wage and amenities between male and female workers. In order to account for other determinants of job change and potentially gender-specific search and mobility constraints, the models control for education, presence of children and marriage status. In addition, since mobility decreases with years since labor market entry, the model controls for a quadratic function of actual experience and years of tenure, and for the number of spells a worker spent out of the labor force. In order to account for labor demand factors, controls also include current occupation (9 categories) and industry (11 categories) dummies, union coverage, employer dimension and the US region-specific annual unemployment rate.[21]

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.[22]

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, showing the Kitazawa (2012) elasticity (or semi-elasticity, depending on the

[21] 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.

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

definition of each regressor) of the rate of job quit.[23]

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 the provision of schedule flexibility. In particular, the average percentage change fall in the probability of job change when a flexible schedule is available relative to when it is not, is 38% higher for women than for men. The percentage change decrease in the probability of quitting a job when parental benefits is, instead, similar for women than for men. The most striking divergence between male and female job quitters, however, concerns of their reaction to a 1% increase in wage. As the first line in table 10 shows, the probability of quitting a job decreases on average by 65% for women following a 1% rise in wage, while it falls by only 38% 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	-0.3818***	-0.6458***
	(0.1343)	(0.1563)
$\mathbf{I}$[Parental Benefits Available at j]	-0.2746***	-0.2672***
	(0.1016)	(0.1027)
$\mathbf{I}$[Flexible Schedule Available at j]	-0.5219***	-0.7214***
	(0.1716)	(0.1645)
Log-Number of Employees at Employer j	-0.1386**	-0.0605
	(0.0543)	(0.0478)
First Child Born by t	-0.3044	-0.5525**
	(0.3197)	(0.2758)
Married by t	-0.6143**	-0.4803**
	(0.2851)	(0.2263)
N	1479	1751
Controls	Y	Y

Notes: 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.

Interestingly, the estimated parameters in table 10 suggest that women and men may both have different preferences for amenities and face different job offer distributions. Regarding

[23] Appendix table 30 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.

the sensitiveness of the probability of job change with respect to job-specific amenities such as schedule flexibility, 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 framework, table 10 results would suggest that young, highly educated and highly labor market attached female workers are more willing than their male counterparts to trade-off wage increases for the provision of schedule flexibility. Men and women, however, are not necessarily subject to the same distribution of job offers. As Light & Ureta (1992) point out, conditional on current experience, a lower (higher) average sensitiveness of quit with respect to wages may signal a higher (lower) ability to find more attractive outside labor market opportunities, conditional on one own current position. The strong and negative estimated wage elasticity of women's quit probability suggests that, conditional on current wage, current experience, and current job benefits, male workers may find it easier to search for, and obtain, lucrative job offers compared to female workers. This result corroborates the idea that male and female workers may obtain structurally different wage offers.

The body of evidence collected in this section highlights two main facts. First, even considering 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. Such factors, however, are unobserved and their impact on the pay gap cannot be quantified by solely relying on descriptive analyses. For these reasons, in the next sections I estimate a search model that allows to quantify the extent to which male and female workers differ in terms of search frictions, preferences, and job offers received in their early careers. I then calculate the contribution of these three factors on the early career gender pay gap.

5 Hedonic Search Model

5.1 Model Setup

I now illustrate the model proposed by Bonhomme & Jolivet (2009), and explain how I allow for gender-specific preferences for amenities, search frictions and job offer distributions.

The setup of the model is as follows. There are two separate labor markets, one for male (m) and one for female (f) workers. I denote workers' gender by g. Within each labor market, there are a continuous mass of workers and a continuous mass of firms. Both employed and unemployed workers search for jobs. An employed worker obtains an outside offer at rate λ_1^g while the arrival rate of offers for unemployed workers is λ_0^g. Jobs can be destroyed. In this event, workers either lose their job (at rate q^g), or contemporaneously obtain an outside job offer (rate λ_2^g).[24]

A job consists of a bundle $(w, \mathbf{a})$ and the offer of jobs follows a cumulative distribution $F^g(w, \mathbf{a})$, 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 $g \in \{f, m\}$ superscript formalizes labor market gender segregation.

When employed, workers obtain utility from (log) wage (w) and a vector of amenities ($\mathbf{a} = [a_1, ..., a_K]$). The main amenities of interest are represented by two dummy variables taking value 1 if an employer offers, respectively, parental leave (either paid or unpaid) and flexible schedule. In the model I estimate, however, I also control for whether employers provide or sponsor child care, and for whether a job requires long work-hours. The addition of further, meaningful job characteristics is necessary because employers tend to jointly offer complementary amenities. As an example, male workers in my sample typically work longer hours compared to women. At the same time, they are more likely to be employed in jobs providing schedule flexibility. Possibly, employers requiring employees to work long-hours are more prone to allow their workers to flexibly manage their own schedule. Not controlling for work hours may then bias the estimated workers' preferences for flexibility, and the wage gains and losses associated with the provision of this amenity. Workers utility function takes the following form

$$u^g(w, \mathbf{a}) = w + \delta^{g'} \mathbf{a} \tag{9}$$

Utility parameters are allowed to vary between female and male workers. For each $a_k \in \{a_1, ..., a_K\}$, δ_k^g represents workers' marginal utility of a_k, corresponding to their marginal willingness to pay out of wage in exchange for the provision of amenity a_k.

I next characterize the steady state of the model. First, the steady state probability that a worker leaves their job is

$$P^g(\text{leave}|w, \mathbf{a}) = q^g + \lambda_2^g + \lambda_1^g \bar{F}_u^g(w + \delta^{g'} \mathbf{a}) \tag{10}$$

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

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

[24] The λ_2^g 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.

$$\lambda_0^g U^g = q^g(1 - U^g) \tag{11}$$

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

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 $G^g(.|\text{car}_{occ}, \text{car}_{ind}, b)$ the distribution of jobs across employed workers of a certain gender and $G_u^g(.|\text{car}_{occ}, \text{car}_{ind}, b)$ the observed distribution of utility levels across workers in the same group, at steady state

$$\begin{aligned}\lambda_0 U F_u(u|.) + \lambda_2 F_u(u|.)(1-U)\bar{G}_u(u|.) = q(1-U)G_u(u|.) + \lambda_2 \bar{F}_u(u|.)(1-U)G_u(u|.) + \\ + \lambda_1 \bar{F}_u(u|.)(1-U)G_u(u|.)\end{aligned} \tag{12}$$

Where I dropped the superscript g, as I will from now on, to avoid abuse of notation. The last result further implies

$$G_u(u|.) = \frac{F_u(w + \delta'\mathbf{a}|.)}{1 + k\bar{F}(w + \delta'\mathbf{a}|.)} \tag{13}$$

where $k = \lambda_1/(q + \lambda_2)$. Also, as Bonhomme & Jolivet (2009) show,

$$\frac{g(w, \mathbf{a}|.)}{g_u(w + \delta'\mathbf{a}|.)} = \frac{f(w, \mathbf{a}|.)}{f_u(w + \delta'\mathbf{a}|.)} \tag{14}$$

The results above imply that it is possible to map the observed gender-specific cross section of $(w, \mathbf{a})$, G, to the unobserved gender-specific job offer distribution F as

$$g(w, \mathbf{a}|.) = (1 + k)\frac{f(w, \mathbf{a}|.)}{[1 + k\bar{F}(w + \delta'\mathbf{a}|.)]^2} \tag{15}$$

Where $k = \frac{\lambda_1}{q+\lambda_2}$ is a measure of gender-specific 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. $\bar{F}(u|.) = 1 - F(u|.)$, is the probability of receiving a job offer providing utility higher than the utility level obtained at current job.

Equation 15 shows that the Bonhomme & Jolivet (2009) model highlights that the relation between wages and amenities observed in the data depends not only on workers' preferences (through δ), but also on search frictions (through k) and on the distribution of job offers that workers face (through f and $\bar{F}$). It further highlights that residual differences in pay between otherwise similar male and female workers may be driven by the same three factors.

5.2 Model Estimation

In order to estimate the model, 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.[25]

Regarding workers and jobs, I keep information about wage and job or employer characteristics. The amenities of interest are measured by dummy variables indicating whether parental leave (either paid or unpaid), and flexible schedule are (individually) available at current employer. In addition, I allow workers to have preferences for childcare provision and for long hours (average weekly hours worked at current job above 45).

Differently from the most sophisticated estimation procedure 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 classes. Workers' careers are proxied by the occupation and industry in which workers are employed for the longest amount of time by the fifth year in 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

[25] Bowlus (1997) shows that part of the gender pay gap between US college graduate workers belonging to the baby boomer generation depended on women's low search effort when out of the labor market relative to when in unemployment. In my sample, however, labor market statuses and transitions in and out of employment and in and out of the labor force are virtually identical between men and women throughout the entire career-span that I use in the structural estimation. I provided this evidence in section 3.3. For this reason, the model I estimate does not allow for different search behaviors between the unemployed and workers out of the labor force.

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 Maximum Likelihood estimation requires econometric assumptions on how firms determine wages and amenities offers. I allow workers' ability b and careers to affect both the offered wage and the associated amenities.

$$w^*(b, \text{car}_{occ}, \text{car}_{ind}) = \mu_0^w + \mu_1^w b + \rho' \mathbf{a}^* + \sum_{occ=1}^{3} \varphi_{occ}^w \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^w \text{car}_{ind} + \sigma_w \varepsilon_w \tag{16}$$

$$a_k^*(b, \text{car}_{occ}, \text{car}_{ind}) = \mathbf{1}\{\mu_0^{a_k} + \mu_1^{a_k} b + \sum_{occ=1}^{3} \varphi_{occ}^{a_k} \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{a_k} \text{car}_{ind} + \varepsilon_{a_k} > 0\} \tag{17}$$

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 wage offers $w^*(b, \text{car}_{occ}, \text{car}_{ind})$ depend on the amenities that a firm offers through the $(K \times 1)$ coefficient vector ρ, that can vary across genders. The second equation represents the factors affecting the provision of each 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. Following Bonhomme & Jolivet (2009), I can now calculate the likelihood function. The contribution of a worker in the cross-section of $(w, \mathbf{a})$ in t_0, the first month a worker is observed, is

$$l_{t_0} = \left(\frac{q}{\lambda_0 + q}\right)^{1-e_{t_0}} \left(\frac{\lambda_0}{\lambda_0 + q}\right)^{e_{t_0}} g_{t_0}(w_{t_0}, \mathbf{a}_{t_0}|.)^{e_{t_0}} \tag{18}$$

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 worker to the likelihood in the next period depends on time t transitions and can be written as

$$\begin{aligned}
l_{t+1} = {} & q^{ju_t} [1 - \lambda_0]^{uu_t} \times \\
& \times \lambda_0^{uj_t} f_{t+1}(w_{t+1}, \mathbf{a}_{t+1}|.)^{uj_t} \times \\
& \times [1 - \lambda_1 \bar{F}(u_t|.) - \lambda_2 - q]^{s_t} \times \\
& \times [\lambda_1 \mathbf{1}\{w_{t+1} + \delta' \mathbf{a}_{t+1} > w_t + \delta' \mathbf{a}_t\} + \lambda_2]^{jj_t} f_{t+1}(w_{t+1}, \mathbf{a}_{t+1}|.)^{jj_t}
\end{aligned} \tag{19}$$

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.

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

$$l(.) = l_{t_0} \prod_{t=t_0}^{T} l_{t+1}(e_{t+1}, w_{t+1}, \mathbf{a}_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, w_t, \mathbf{a}_t, b, \text{car}_{occ}, \text{car}_{ind}) \tag{20}$$

The likelihood function is

$$L(.) = \prod_{i=1}^{N} l_{t_0,i} \prod_{t=t_0}^{T} l_{t+1,1}(e_{t+1}, w_{t+1}, \mathbf{a}_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, w_t, \mathbf{a}_t, b, \text{car}_{occ}, \text{car}_{ind}) \tag{21}$$

As in Bonhomme & Jolivet (2009), I can find the functional forms for $f(w^*, \mathbf{a}^*|.)$ and $\bar{F}_u(u|.)$ that appear in equation (19) and, consequently, in equation (21), because of the assumptions of normality and independence of the unobservables in the job offers.[26]

Given the likelihood function, I can implement the sequential maximum likelihood algorithm described by Bonhomme & Jolivet (2009) to estimate the parameters of the wage offer distribution and the search and preference parameters. First, the 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.

I estimate θ, the parameters of the job offer distribution by maximizing $L_1(\theta)$ for workers who move out of unemployment. Second, I substitute the estimated parameters $\hat{\theta}$ into $L_2(.)$ and $L_3(.)$, and estimate λ and δ following an iterative procedure. In particular, for a guessed vector of preferences $\tilde{\delta}$, I estimate the λ. Given the estimate $\hat{\lambda}$, I then estimate workers' preferences by maximizing the likelihood that workers stay at their current job or switch job with respect to δ.[27] I estimate the model separately for men and women.

[26] Appendix Section H1 shows how to derive the functional forms for $f(w^*, \mathbf{a}^*|.)$ and $\bar{F}_u(u|.)$.

[27] Appendix Section H2 describes the estimation procedure in greater detail.

5.3 A Discussion on Identification

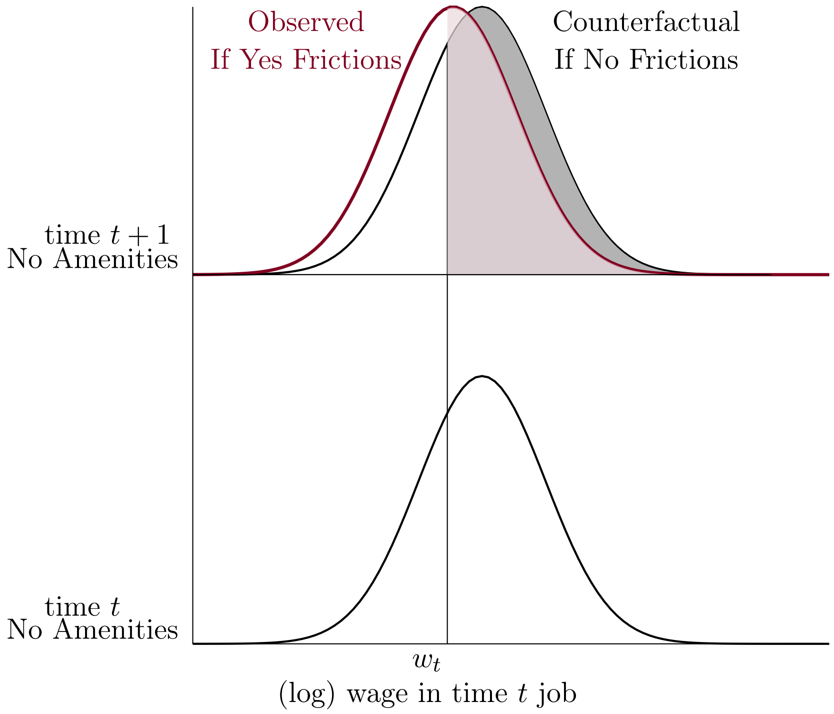
The identification of the parameters of interest requires features that the NLSY97 data provide. In particular, it is crucial for identification purposes that both movements in and out of employment and movements across jobs can be observed, ideally at a high frequency. The high frequency of the 64-months dataset I construct using the NLSY97 weekly arrays ensures that estimates of the search frictions parameters do not suffer from strong time-aggregation biases. Most importantly, the possibility to track workers as they move both across employers and across labor market statuses is key to separately identify workers' preferences and the features of the wage offer distributions they face for jobs that either do or do not provide amenities.

Identifying the features of the job offer distribution requires the assumption that the labor market is in equilibrium. In a search framework *à la* Burdett & Mortensen (1998), a labor market equilibrium implies that no employer offers a wage below workers' reservation wage, otherwise they would not be able to attract any employee. In a hedonic search framework *à la* Hwang, Mortensen & Reed (1998) such the one modeled here, the assumption of labor market equilibrium implies that no employer offers a wage-benefits package whose value to the workers is lower than their reservation utility. It implies that unemployed workers accept any job they are offered, as any job entails at least their reservation utility. For this reason, workers' preferences over wages and non-wage benefits do not affect workers' movements from unemployment to employment. Hence, transitions into employment identify the parameters of the job offer distributions that gender-specific workers face. The main parameters of interest are the mean wage offered in different careers to men and women in jobs that do not provide benefits, the mean wage offered in jobs that do provide either flexibility or parental leave (or both), and the wage dispersion of job offers.

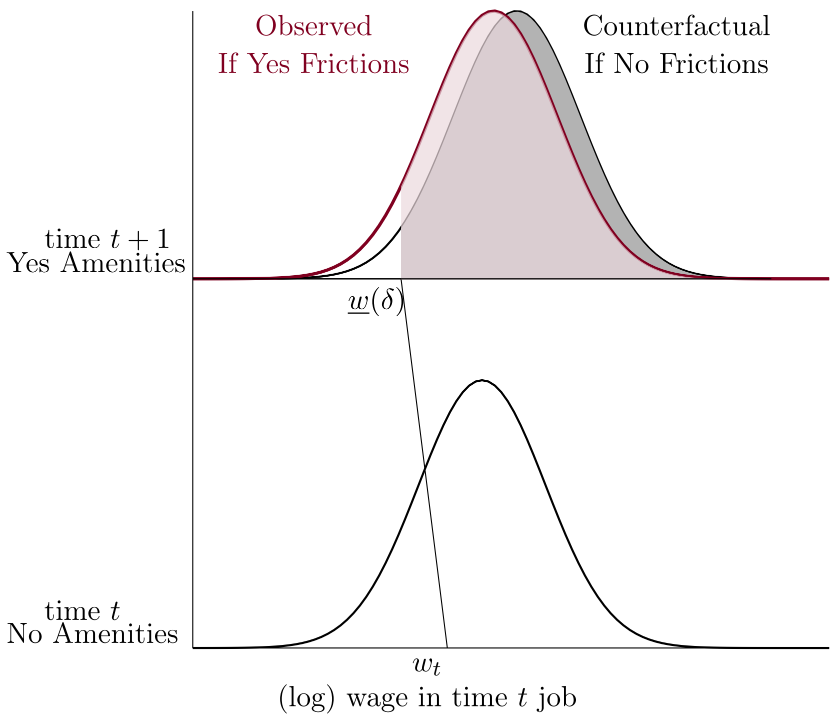
Given the identified parameters of the gender and career specific job offer distributions, $F(.)$, movements across any other labor market status and job-to-job movements allow to identify the search frictions parameters. The required identification assumption consists of imposing that the movements across labor market statuses and employers observed in the data are no motivated by any factor external to the model. Under this assumption, the monthly probability of receiving a job offer when out of employment, λ_0, is simply identified using the frequency of workers who remain unemployed for two consecutive months. The job destruction rate, q, is identified using the frequency of workers who exit employment on a monthly basis.

For a certain, assumed, preference parameter vector δ, the monthly arrival rate of an utility-enhancing job offer, λ_1, can be identified by comparing the probability of job-to-job transitions if $\lambda_1 = 1$, with the probability of job-to-job transitions in the data.

Figure 4: The Identification of λ_1 - An Illustration



(a) Job-to-Job Transitions: No Amenities in t, No Amenities in $t+1$



(b) Job-to-Job Transitions: No Amenities in t, Yes Amenities in $t+1$

Notes: The figure in panel (a) illustrates the argument for the identification of λ_1 using month-to-month movements of employees across jobs that do not provide amenities. The figure in panel (b) illustrates the argument for the identification of λ_1 using month-to-month movements of employees from jobs that do not provide amenities to jobs that do provide amenities.

Consider, in particular, the probability that a worker earning (log) wage w_t in a job that does not provide amenities moves into a different job that does not provide amenities between t and $(t+1)$. If λ_1 were equal to one, the probability of a voluntary job-to-job transition should equal $\bar{F}_{t+1}(w_t|\mathbf{a}=0,.)$. If search frictions exist, however, this probability equals $\lambda_1\bar{F}_{t+1}(w_t|\mathbf{a}=0,.)$. If so, the probability of job-to-job transitions in the data (pink area in figure 4 panel (a)) should be lower than the counterfactual job-to-job transition probability that would be observed in absence of frictions (gray area in figure 4 panel (a)) by a factor of λ_1. Consider, now, the probability that a worker earning w_t in a job that does not provide amenities moves into a job that does provide amenities between t and $(t+1)$. Imagine for simplicity that there is only an amenity of interest. If λ_1 were equal to one, the probability of a voluntary job-to-job transition of this type should equal $\bar{F}_{t+1}(\underline{w}(\delta)+\delta|\mathbf{a}=1,.)$. Hence, assuming a value for δ, yields $\underline{w}(\delta)$, the minimum wage that a worker would accept to voluntarily change job in exchange for the provision of the amenity of interest. If the amenity is valuable, $\underline{w}(\delta)$ can be lower than time t worker's wage. In presence of search frictions, however, the probability of such job-to-job movement becomes $\lambda_1\bar{F}_{t+1}(\underline{w}(\delta)+\delta|\mathbf{a}=1,.)$. The ratio between the observed and the frictionless theoretical job-to-job transitions identifies λ_1. This argument is illustrated in figure 4 panel (b).

The identification of λ_1 allows to identify λ_2, the monthly probability of making a constrained job-to-job transition, using the share of workers in the data who change jobs to enter a new employment relationship that entails a wage lower than $\underline{w}(\delta)$.

The identification of the δ parameter vector of preferences, finally, follows a revealed preferences approach. Having identified λ_1, λ_2 and the features of the job offer distribution, observing the wages and amenities packages of workers in the data who either change their job, $(\lambda_1+\lambda_2+\bar{F}_{t+1}(\underline{w}(\delta,\mathbf{a})+\delta\mathbf{a}|.))$, or stay on their current job, allows to identify the minimum wage that workers would accept in the exchange for the provision of an amenity and, consequently, workers' marginal willingness to pay for it, δ.

This discussion should clarify why a structural model that allows for gender differences in preferences, search frictions, and job offers distribution is required to cleanly separate the impact of gender-specific constraints from the impact of gender-specific preferences on the gender wage gap. Inferring women's preferences for amenities from the probability of changing a higher-pay job for a lower-pay job that provides a certain benefit, produces biased estimates due to the unobserved difference in the distribution of wages that men and women draw their offers from. Such bias would increase in the gender difference in the mean wage offered to male and female workers conditional on the provision of amenities.

6 Results

6.1 Parameter Estimates

Tables 11, 12 and 13 report the structural parameter estimates.[28] Regarding search frictions, Table 11 shows that the main difference between male and female workers concerns the monthly probability of obtaining a job offer when unemployed. The probability is about 20% for women and 24% for men.[29]

Table 11: Estimated Search Frictions Parameters

	λ_0	λ_1	λ_2	q
		Females		
Coeff.	0.199	0.013	0.005	0.008
Asy.Std.Err.	(0.013)	(0.002)	(0.001)	(0.001)
		Males		
Coeff.	0.236	0.014	0.005	0.007
Asy.Std.Err.	(0.018)	(0.002)	(0.001)	(0.001)

Notes: National Longitudinal Survey of Youth, 1997. Search frictions parameters estimated through Sequential Maximum Likelihood. Asymptotic Standard Errors in parentheses.

The result is particularly interesting in light of the descriptive evidence collected in section 3.2. Since male and female workers in the sample are similar in terms of labor market and work attachment during the first five years of their career (the time interval I consider in the structural analysis), it is unlikely that young women out of work receive job offers at a lower rate because they search less intensively than men, or because they are willing to stay out of the labor market. When employed, instead, male and female workers face similar search environments. The probability of receiving job offers (λ_1), the rate of job destruction (q) and the rate of constrained job-to-job transitions (λ_2) are very similar across genders.

Regarding preferences, the estimated coefficients in Table 12 panel (a) show that workers attach a high value to the provision of both parental leave and schedule flexibility. At the same time, the results do not support the idea that any observed difference in wages between male and female workers can be rationalized by large underlying differences in preferences for amenities. Overall, workers' estimated preferences for amenities are strong for both genders.[30]

[28] Table 11 reports the asymptotic standard errors in parentheses, and tables 12 and 13 report the likelihood ratio tests p-Values in brackets. For each likelihood ratio test, the restricted likelihood is maximized by imposing that the parameter indicated in the respective column equals zero. I rely on likelihood ratio tests to infer the statistical significance of the model's preference and job offers parameters. The small number of individuals included in the estimation makes inference based on asymptotic standard errors problematic. The asymptotic likelihood ratio test has more power, hence it is more reliable in small samples.

[29] This result is consistent across different specifications of the model, and it is stable irrespective of whether the model accounts for within genders heterogeneity in terms of ability and career.

[30] The magnitude of the estimated preferences coefficients is consistent with the magnitude of the preferences for

Table 12: Estimated Marginal Willingness to Pay for Amenities

	Estimated Preferences Parameters $\hat{\delta_k}$		The Wage Value of Amenities $e^{-\delta_k}$	
	Males	Females	Males	Females
Flexibility	0.825	0.814	0.438	0.443
LR Test p-Value	[0.000]	[0.000]		
Parental Leave	1.140	1.311	0.320	0.269
LR Test p-Value	[0.000]	[0.000]		

Notes: National Longitudinal Survey of Youth, 1997. Preference parameters estimated through Sequential Maximum Likelihood. 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. Table 31 in the Appendix shows the coefficient estimates for workers' preferences for long hours and child care provision. The wage value of amenities is the minimum wage that a worker would accept in the exchange for a provision of a certain amenity, relative to the wage that would provide the same utility in a job that does not provide any amenity. $e^{-\delta_k} = \frac{w(a_k=1,u)}{w,(a_k=0,u)}$

From workers' point of view, schedule flexibility and parental leave are the most relevant non-wage amenities. The estimated preference coefficients, $\hat{\delta}_f$ and $\hat{\delta}_l$, are positive, implying that both young men and women prefer jobs providing these benefits over jobs that do not, and their magnitudes show that preferences are only slightly heterogeneous across genders. As panel (b) shows, in order to have a flexible work schedule, male workers would accept 43.8% of the hourly pay they would accept in a job that does not provide such benefit. The figure is 44.3% for women. In order to obtain parental leave, young men would accept 32% of the hourly wage they would accept in a job that does not provide this benefit, while 27% is the ratio for women.[31]

Table 13 reports the estimated features of the distributions of wages offered to male and female workers.[32] While labor demand is only modeled in reduced form, calling for caution in the interpretation of these estimates, they nevertheless suggest that male and female workers face dissimilar prospects when entering the labor market. First, the estimated μ_0^w and φ^w parameters show that, on average, the job offers that female workers receive, involve lower wages relative to the jobs offered to male workers. For workers in some careers only, the wage offers gap reverses in the upper part of the *ability* distribution due to the higher *ability* wage premia that women enjoy (μ_1^w). Second, the wage penalties and premia associated with the provision of amenities and contractual benefits are heterogeneous across genders.

amenities such as job security, that Bonhomme & Jolivet (2009) estimate on a sample of European men.

[31] As table 31 in the Appendix shows, male workers are estimated to prefer working long hours more strongly than female workers, but the coefficient is positive for both genders. This result implies that workers are willing to accept wage cuts in order to work more hours. It is possible that jobs requiring young employees to work long hours offer higher chances of promotion and faster wage growth to workers who accept to exert high effort on the job (Gicheva 2013), or other unobserved benefits whose value is captured by $\hat{\delta}_h$. The estimated coefficients capturing preferences for childcare provision are also positive for both male and female workers, but statistically indistinguishable from zero, possibly due to the small number of jobs offering this amenity in the data. 20% of employed women and 16% of employed men in my sample work for employers providing child care.

[32] The structural parameter estimates regarding the offer of amenities are reported in the Appendix Section H3.

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}^w	φ_{oth}^w
						Females						
Coeff.	2.318	0.420	-0.025	-0.100	0.279	0.015	-0.010	0.090	-0.381	0.040	0.262	0.100
LR Test p-Value	[0.000]	[1.000]	[0.300]	[1.000]	[0.000]	[0.510]	[1.000]	[0.100]	[1.000]	[0.300]	[1.000]	[0.57]
						Males						
Coeff.	2.793	-0.069	0.110	-0.070	0.313	0.013	0.171	0.329	0.009	-0.004	0.036	-0.111
LR Test p-Value	[0.000]	[0.186]	[0.011]	[0.000]	[0.000]	[1.000]	[0.000]	[0.000]	[1.000]	[1.000]	[1.000]	[0.081]

Notes: National Longitudinal Survey of Youth, 1997. Asymptotic standard error 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. μ_0^w is the estimated average wage offer parameter, μ_1^w is the wage premium for ability, the ρ parameters estimate the change in the mean wage in jobs that offer, respectively, flexibility (f), long hours (l), parental leave (p) and child care (c). The φ parameters measure the change in the average wage offer between jobs in the excluded occupation category and jobs in executive occupations (e), professional occupations (p), other occupations (o). The remaining φ parameters measure the change in the average wage offer between jobs in the excluded sector and jobs in finance, information, and real estate (f), trade (t), other sectors(oth)

Regarding schedule flexibility, jobs offering such benefit entail 11 log-points higher wages for male workers, while the availability of a flexible work schedule comes at no wage gain for female workers (ρ^f). Jobs providing parental leave, instead, offer considerable wage gains to both men and women (ρ^l). Yet, the premium associated with working for an employer providing parental leave is 3.4 log-points higher for men.

Since parental leave is the most valuable amenity from workers' point of view, and its provision is costly for employers, the wage premia associated with such benefit suggest that both male and female workers are able to progressively select themselves into better jobs. In fact, the evidence of wage premia attached to the provision of amenities that positively accrue to workers utility, suggests that better and more productive firms are more likely offer both higher wages and better working conditions to their employees. This implication is both consistent with the Hwang, Mortensen & Reed (1998) model, and in line with the vast anecdotal evidence suggesting that well-established and successful firms are more likely to try to retain workers by offering parental leave.[33]

Schedule flexibility is also a valuable benefit from workers' perspective. The pay premium estimated for male workers in jobs that provide such benefit, is in line with the idea, supported by anecdotal evidence, that more productive employers face lower costs of providing utility-enhancing amenities, thus offering higher wages and better working environments in order to retain their employees.[34] The estimates for female workers, instead, show that women do not obtain any wage gains, and may incur wage losses, when they are allowed to work on a flexible

[33]See, for example, Claire Cain Miller, "Lowe's Joins Other Big Employers in Offering Paid Parental Leave", *The Upshot, The New York Times* February 1 2018; and Joann Michelson "Emploee Retention: How Small Companies Can Offer Great Paid-Leave Programs', *Harvard Business Review* January 7 2021.'

[34]See, for example, Sarah Halzack "Workplace Flexibility Can Be Key to Recruiting and Retaining Top Workers", *The Washington Post* December 2 2012

schedule.

Two possible interpretations may rationalize the absence of wage gains for female employees working on a flexible schedule. First, it is possible that firms allowing female employees to work on a flexible schedule are less productive than firms that do not offer such benefit, and thus offer lower wages. Second, some of the women's transitions across jobs that I model as voluntary, may be due to some underlying constraints. This fact is especially plausible in light of the evidence in table 7, showing that transportation costs and family obligations motivate overall 15% of women's job changes. These types of constraints may make it necessary for some women to work on a flexible schedule, and limit their ability to work for employers that do not provide such benefit. When constraints limit the range of women's choices, their labor supply at the firm level is more rigid than men's labor supply (Manning 2003), and employers providing schedule flexibility may use their resulting monopsonistic power to offer women a lower wage relative to the wage they would offer a comparable man for the same position. While a similar argument can explain why women earn less than men in jobs that provide parental leave, it is also worth noting that part of the gender differences in wage offers may be due to unobserved productivity differences among firms.

6.2 The Impact of Frictions, Preferences, Offers on the Gender Wage Gap

In this section, I use the estimated parameters of the model to predict women' s average early-career wage, and the average pay they would obtain in a series of counterfactual scenarios. Specifically, in the first counterfactual scenario, I predict women's career-specific average wage if labor market frictions strongly decreased (table 14, panel (a) line (1)). The second counterfactual exercise predicts women's wages if workers' utility was not affected by benefits and job attributes (table 14, panel (a) line (2)).[35]. In the remaining counterfactual exercises, I predict the wages women would obtain if search environments, preferences, and job offers were the same as men's. In panel (b), I report the gap between women's counterfactual mean (log) wages and women's predicted mean (log) wages.

In order to compute women's predicted and counterfactual wages, I use the appropriate estimated parameters to simulate 100 cross-sections of 1000 female labor market entrants, and to model yearly transitions across employment statuses and across jobs. I perform the simulations separately by careers, defined by sector and occupation. For each year on the labor market, the simulation generates a distribution of employed workers across jobs defined by pay level and amenities. The mean of the t'th year of experience average wage across the 100 career-specific simulations is the predicted wage in t. The mean of the predicted wages within the first five years of experience is the predicted mean early career wage, shown in the first line of table 14.

[35] In this scenario, I assume that the arrival rates of job offers λ_0 and λ_1 double, while the rates of job distruction and of constrained job-to-job transitions decrease by half.

Table 14: Predicted Gender Wage Gap

	(a) Administration, Education Health, Social Services				(b) Financial Services			
	Admin.	Executive	Professional	Other	Admin.	Executive	Professional	Other
Women's Predicted log-Wage	2.789	2.812	2.903	2.437	2.781	2.811	2.903	2.424
Panel (a)	Counterfactual Wage							
(1) Less Search Frictions	2.812	2.834	2.924	2.459	2.801	2.833	2.917	2.444
(2) No Preferences for Amenities	2.806	2.829	2.920	2.453	2.821	2.845	2.932	2.458
(3) $\hat{\lambda}^m$	2.789	2.812	2.905	2.439	2.783	2.815	2.905	2.428
(4) $\hat{\lambda}^m$ and $\hat{\delta}^m$	2.789	2.814	2.904	2.441	2.785	2.815	2.903	2.430
(5) $\hat{\lambda}^m$, $\hat{\delta}^m$ and $\hat{\rho}^m$	2.885	2.926	3.032	2.561	2.879	2.922	3.033	2.553
(6) Men's Predicted log-Wage	2.724	2.937	3.098	2.675	2.729	2.925	3.085	2.683
Panel (b)	Predicted Wage Gap							
(1) Less Search Frictions	0.022	0.022	0.021	0.022	0.020	0.022	0.014	0.020
(2) No Preferences for Amenities	0.016	0.017	0.017	0.016	0.040	0.034	0.029	0.034
(3) $\hat{\lambda}^m$	-0.001	0.000	0.002	0.002	0.001	0.004	0.002	0.004
(4) $\hat{\lambda}^m$ and $\hat{\delta}^m$	-0.001	0.002	0.001	0.004	0.004	0.004	0.000	0.006
(5) $\hat{\lambda}^m$, $\hat{\delta}^m$ and $\hat{\rho}^m$	0.096	0.114	0.129	0.123	0.098	0.111	0.130	0.129
(6) Men's Predicted log-Wage	-0.088	0.103	0.174	0.216	-0.073	0.092	0.168	0.239

Notes: National Longitudinal Survey of Youth, 1997. Actual and counterfactual wages by workers' careers in different scenarios. Counterfactuals are computed assuming that women are homogeneous in ability within careers. The industry and occupation median value of the CAT-ASVAB test percentile is used to define the representative woman in each career.

The first rows in panel (a) and panel (b) of table 14 show that search frictions affect workers' pay. Employed women would earn between 2 and 3 log-points more per hour, on average, if jobs offers arrived at a higher rate and the chances of losing a job halved. A fall in search frictions would make women less likely to enter unemployment, and more likely to obtain utility enhancing job offers. Both circumstances would decrease the chances that women work in low-pay jobs, rise their chances of climbing the job-ladder thus accelerating their returns to labor market experience, and increase the average early-career wage among employed women.

The second rows in panels (a) and (b) show that workers' preferences for amenities do impact their wages. Women in all careers would earn around 2% to 4% more per hour if their utility solely depended on their wages.[36] While this amount may seem quantitatively unimportant, it implies that a representative woman in a full-time full-year job in a certain career is predicted to give up more than $3,000 in the first five years of her career in exchange for the provision of utility-enhancing amenities.

Search frictions and preferences for benefits have a remarkable impact on women's pay. Yet, they do not determine a large share of the gender pay gap between male and female workers (lines (3) and (4)). In some careers only, women would not earn slightly higher wages if they faced men's search frictions. If they faced men's search frictions and shared men's preferences for amenities, the pay gap would not be reduced. This result shows that male and female workers have too similar preferences for benefits such as flexibility and parental leave, for these factors to determine the bulk of the early career gender gap between male and female workers.

While preferences for amenities are similar across genders, women earn less than comparable men when working for employers providing non-wage benefits (panel (a) and panel (b), line (5)). If men and women faced identical job offers, but differed in terms of search and preference parameters, and in terms of the pay penalty/premium associated with the provision of amenities, men would earn 10% to 14% more than women on average. This gap would arise because jobs that provide amenities tend to pay higher wages to men than to women.

The last line in panel (a) reports men's predicted wage by career and shows that male workers are predicted to earn more than women in all but administrative jobs. Specifically, men in executive and professional jobs earn 10% to 20% more than women on average (panel (b) line (6)). This gap arises partly because men are offered higher wages in these careers relative to women and partly due to the higher pay premia that male workers receive in jobs providing amenities such as flexibility and parental leave. Regarding administrative careers, instead, women earn more than men on average, but they earn less than men in jobs providing amenities as well as in jobs that do not provide benefits. Hence, the pay-gap favoring women in administrative jobs is due to a composition effect, and it is mostly driven by the over-representation of female

[36] Given the distribution of job offers and given the probability of constrained job-to-job transitions, no female workers would voluntarily change job if the move implied a wage cut. Hence, in steady state there would be fewer voluntary job-to-job transitions, and the average wage would be higher.

administrative workers in workplaces offering both amenities such as parental leave, and higher wages. While I cannot discern it from the data, it is reasonable to guess that that these women may predominantly work in the public sector.

The results in table 14 provide evidence that gender specific wage offers explain virtually the entire gender pay gap between young male and female workers and exacerbate it in jobs providing benefits such as flexibility and parental leave. In other words, the price that workers seem to pay for the provision of amenities is higher for women, irrespective of a strong similarity in the marginal willingness to pay across genders. This determines the bulk of the early career pay gap that the model predicts. Importantly, the weighted average of the early-career pay gap across occupations and industries amounts to 4.3 log points. The gap is only 1 log-point higher than the composition adjusted pay gap in the first five years of experience, whose path is plotted in figure 1.

6.3 The Impact of Frictions, Preferences, Offers on the Gap's Expansion

Figure 5 plots the growth path of the early-career wages predicted by the model.[37] The growth paths are computed by simulating the predicted and counterfactual wages that the woman with mean CAT-ASVAB percentile test score in her industry-occupation class would obtain in each year of experience. The weighted average of the industry-occupation specific wage growth paths is reported in figure 5, where the weights used are the shares of women in each industry-occupation career.

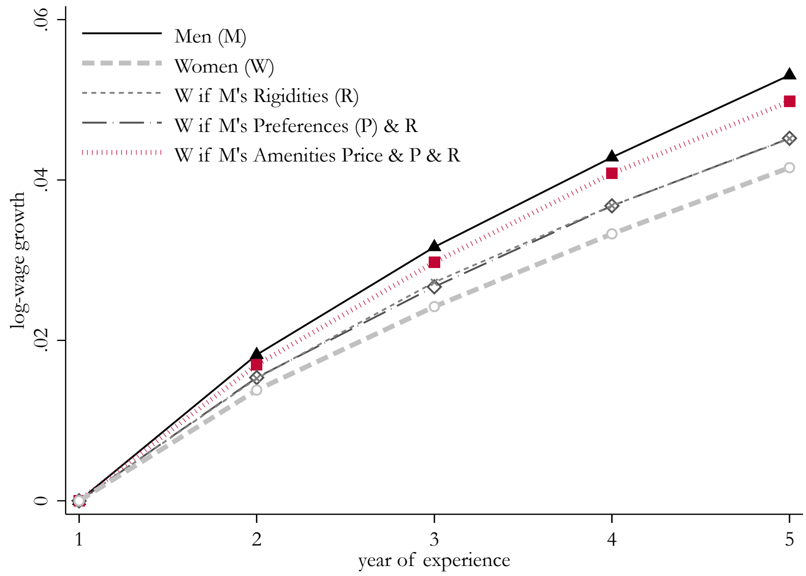
In the figure, the thick, dashed, lightgray line represents the predicted (log) wage growth path for the average woman, while the solid, black line represents the counterfactual, predicted wage growth path that the average woman would experience if she shared men's preferences, search frictions, and wage offers, and if the distribution of men across occupation-industry classes corresponded with the occupation-industry distribution of women. As the graph shows, women's wages grow more slowly than men's wages in all careers, which generates a 1.2 log-points expansion of the pay gap by the fifth year of labor market experience. It implies that the model explains 25.6% of the 3.9 log-points wage gap increase observed in the data and reported in figure 1. The remaining part of the growing wage gap is likely due factors such as gender-differences in selection across occupations, in returns to tenure and in the likelihood of obtaining promotions (Gicheva 2013, Booth, Francesconi & Frank 2003), that I do not model.

In figure 5, the thin, short-dashed line plots the wage growth that the average woman would earn if she faced the same search frictions as a virtually identical man. According to the model estimates, men face slightly lower search frictions relative to women. In particular, they are significantly more likely to obtain wage offers when out of work. In a Burdett & Mortensen

[37] The career-specific predicted and counterfactual wage growth paths for female workers are reported in figures 8, 9, 10 and 11 in the Appendix.

(1998) framework, this should make their experience profile steeper. The higher chances of receiving job offers, in fact, should make unemployment more valuable to men, thus contributing to increase their reservation wages. Consequently, this would shift up the wage distribution that male workers face relative to women, thus also increasing their returns to search and job changes. If women faced men's search frictions, then, their wages would rise faster. The estimated gender differences in search frictions explain 33% of the 1.2 log-point predicted increase in the early career pay gap, and 8% of the rise in the pay gap observed in the data.[38]

Figure 5: Predicted Log-Wage Profiles



Notes: National Longitudinal Survey of Youth, 1997. Model predicted wage growth path for the career-specific representative woman, and counterfactual wage paths. The predicted and counterfactual wage growth paths are constructed by weighting the contribution of wage paths in different careers by the share of female workers in that career. The wage paths are computed for the representative woman in each career, the latter being defined as the woman with the mean CAT-ASVAB test score percentile in each industry-occupation class.

The longdashed, dark-gray line plots the counterfactual wage growth path for the average woman if she shared men's search frictions and preferences for amenities. As the figure shows, the wage growth path would not change in this counterfactual scenario, relative to the wage growth that women would experience if sharing men's search frictions only. This result further corroborates the evidence that preferences for amenities do not determine the early career gender pay gap. In fact, women are not disproportionately more likely than men to switch job in order to be provided a certain amenity even at a higher wage cost.

Women, however, do pay a higher price for the provision of both parental leave and schedule flexibility. Consequently, their average early-career wage and their returns to experience would both increase in the counterfactual scenario where women's mean offered wage in amenities-

[38]The contribution is computed by taking the ration between the overall early-career wage growth experienced by the counterfactual woman facing men's rigidity, and the predicted women's wage growth path.

providing jobs equaled the mean wage offered to men. The red, dotted line in figure 5 shows that the portion of the wage-gap growth left unexplained by search frictions is almost entirely explained by the differential prices that men and women pay for the provision of amenities. The price of amenities, in fact, explains 42% of the early-career predicted wage gap growth, and 10.5% of the wage gap growth in the data. It means that, although women progressively climb the job ladder by entering employment relationships in firms that offer benefits and higher wages, the wage gap in wage offers rises with respect to men when employers provide amenities. Consequently, while women's wages grow over time due to job changes, they do not grow as fast as they grow for men. Finally, women are offered lower wages in jobs that do not provide amenities too. The gap in these wage offers, however, explains only 25% of the overall predicted wage gap growth, and 6% of the wage-gap growth observed in the data. As a matter of fact, although the baseline wage offers that men and women receive are strongly different, throughout their early careers, both men and women progressively move towards jobs that do offer benefits. Hence, it is workers' entry into higher-pay jobs providing amenities that determines the bulk of wage growth for both men and women. At the same time, it is the difference in the wage offered to men and women in jobs that do provide amenities to determine the larger portion of the increase in the early career pay gap.

Overall, the model shows that the lower wage offers received by women in jobs that do provide flexibility and parental leave relative to men are the main factor explaining both the average early-career pay gap and its increase over years of experience soon after labor market entry. While search frictions also explain part of the pay-gap increase, as they make it harder for women to climb the job ladder, women are not more willing than men to forgo wage gains in exchange for the provision of flexibility and parental leave. Being preferences for these amenities highly homogeneous across genders, preferences do not play any relevant role in explaining the rising gender pay gap over workers' early career. These results are in line with the results that Liu (2016) provides in his estimation of workers' preferences for part time work.

Importantly, as the wage gap arises as a consequence of the wage offers that men and women are subject to, rather than as a consequence of gender-specific preferences, the early career gender pay gap is not an outcome of wage differentials compensating for gender differences in preferences for flexibility and parental leave. Women, in fact, pay a higher price for benefits they prefer as strongly as men. As a consequence, the overall utility that women obtain from their employment relationships is lower, on average, than the average utility that men obtain from their jobs. The model-predicted decomposition of the average gender gap in the utility obtained from employment relationships is shown in Appendix section H.

While a full analysis of the reasons determining differences in the wage offers that men and women receive is beyond the scope of this paper due to data limitations, it is worth noting that these may be due to different factors. On the one hand, if women are more constrained in their job search compared to men, they may be offered lower wages due to monopsonistic discrimination. On the other hand, statistical discrimination may partly explain the gender differences in wage offers I estimate if employers expect women to incur more career interruptions and invest less in their human capital development. It is also possible that part of the gender differences in wage offers that I estimate is due to factors that I cannot control for in my analysis. As an example, Le Barbanchon, Rathelot & Roulet (2021) use French administrative data to show that 14% of the residual wage gap is explained by gender differences in wage offers due to underlying differences between men and women in preferences for commuting. In a study on the employment outcomes of Boston University's Questrom School of Business, instead, Cortes, Pan, Pilossoph & Zafar (2021) provide evidence that stronger risk aversion among young women causes them to accept job offers earlier than men and to forgo potential wage gains from additional search that partly explain the early-career gender pay gap. In light of these analyses, one might ask to which extent monopsonistic discrimination matters in determining the lower wages offered to young American women compared to their male counterparts, vis à vis alternative explanations including statistical discrimination, preferences for commuting and risk aversion. While I acknowledge that it is not possible to disentangle the impact of these different factors on wage offers in the framework I propose in this paper, I plan to address these limitations in future work.

7 Conclusions

In this paper I studied a recent generation of young, college graduate workers entering the United States labor market since 2000, and showed that a gender pay gap arises during workers' early careers and increases over time, even between male and female workers who are equally educated and willing to participate to the labor market. I also showed that job changes explain a non-negligible part of the early career wage gap and that, controlling for a number of individual and job specific characteristics, job search and job changes entail significantly higher wage gains for men than for women. Finally, I showed that female workers' job quit probability 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 further improve their pay by climbing the job ladder.

Motivated by this evidence, pointing to the possibility that differences in search frictions, preferences for non-wage attributes, and jobs offers, explain the early career gender wage gap, I estimated a model of hedonic job search and 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 comparable in terms of preferences for job attributes such as flexibility and parental leave, suggesting that the early career wage gap observed in the data cannot be explained by compensating wage differentials. Women, however face stronger search frictions than men, and are significantly less likely to receive job offers when out of work. Furthermore, job offers are remarkably different across genders. Women tend to receive offers entailing lower wages relative to men, and predominantly so when parental leave and schedule flexibility are provided.

Overall, the model I estimate explains 25.4% of the early-career growth in the gender wage gap observed in the data. This result is both economically meaningful and credible, since it is well known that a large portion of the pay gap comes from gender-based differences in occupational choices (Goldin 2014, Blau & Kahn 2017), and by differences across genders in returns to tenure (Barth, Olivetti & Kerr 2021) and in the likelihood of obtaining promotions (Booth, Francesconi & Frank 2003, Gicheva 2013). My structural estimates imply that the higher price that women pay for amenities determines 42% of the early career increase in the pay gap that the model predicts, and 10% of the increase in the pay gap observed in the data. As workers climb the job ladder, they progressively enter jobs that offer both high wages and better benefits packages. However, the lower wage offers that female workers receive in amenity-providing jobs, compared to men, entrenches the former's wage growth prospects through job changes. For this reason, the search for amenities determines the bulk of the early career gender pay gap growth. 33% of the growth in the model-predicted pay gap is due to the stronger search frictions that out-of-work women face, depressing their chances of receiving a job offer, their reservation wage, and the wage offers they obtain as a consequence. Finally, 25% of the growth in the gender wage gap is predicted, in the model, by the lower wage offers that women obtain in jobs that do not provide amenities.

The results of this paper are relevant for three main reasons. First, by complementing Liu (2016) findings that gender-specific preferences for part-time work do not determine the bulk of the gender wage gap, I show that similar conclusions can be reached when comparing highly similar, strongly labor market attached workers, and analyzing preferences for amenities that may be particularly valuable to workers who are willing to invest in own careers: flexibility and parental leave. Second, by studying workers' careers since labor market entry, I am able to show that the search for amenities, and the higher price that women pay for flexibility and parental leave, irrespective of their preferences, is a non-negligible factor in explaining the opening-up of the gender pay gap among highly educated workers. Third, by showing that differences in wage offers determine most of the gender pay gap at the very beginning of workers careers and its growth, before labor supply behavior begins to differ across genders, and in spite of a strong degree of similarity in the type and frequency of job-to-job and labor market transitions between male and female workers, the results of my analysis support the idea that monopsonistic discrimination in wage offers should not be excluded as an explanation of the residual wage gap among highly similar male and female workers.

If the gender-differences in wage offers I estimate are at least partly due to monopsonistic discrimination in wages, the evidence that the pay gap is exacerbated among strongly committed workers in jobs offering flexibility and parental leave suggests that policies that subsidize employers' cost of providing certain amenities could be effective in reducing the pay gap. As a matter of fact, such policies would make valuable benefits more broadly available, thus reducing the constraints that may otherwise reduce the set of jobs women can choose their offers from. This conclusion is primarily relevant as far as paid parental leave is concerned. In fact, while in March 2021 the US President Joe Biden proposed to reform the Family and Medical Leave Act to provide 12 weeks of paid parental leave to eligible American workers, to this date the United States are still the unique high-income country not having enacted any paid parental leave policy at the national level.[39]

[39] The proposal to mandate and subsidize paid parental leave at the Federal level was not included within the framework of the "Build Back Better" public investments plan that President Joe Biden announced on October 28, 2021.

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Appendix

A 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. 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).

A2. 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 3.

B Sample Characteristics

Table 15: Time-Invariant Sample Characteristics - All Races and Ethnicities

	Males	Females	Diff.	Obs.
Age at labor market entry	24.23	24.33	-0.10	984
No more in education by labor market entry	0.65	0.57	0.07**	984
Enrolled in school at labor market entry	0.19	0.20	-0.01	984
Bachelor degree by labor market entry	0.71	0.77	-0.07**	984
Master degree by age 26	0.07	0.10	-0.04**	984
Prospective PhD graduate	0.02	0.02	-0.00	984
Married/cohabiting by labor market entry	0.26	0.37	-0.11***	984
Married/cohabiting by 3rd yr in labor market	0.46	0.56	-0.10***	984
Married/cohabiting by 5th yr in labor market	0.63	0.67	-0.04	984
Married by 2015	0.66	0.64	0.01	984
Has child by labor market entry	0.06	0.10	-0.04**	984
Has child by 3rd yr in labor market	0.13	0.17	-0.04	984
Has child by 5th yr in labor market	0.24	0.27	-0.04	984
Has child by 2015	0.53	0.57	-0.04	984
Age at first child birth	28.05	27.29	0.76**	544
Total number of jobs held	2.49	2.43	0.06	984
Changes employer by 5th year in labor market	0.53	0.52	0.01	984
Year of experience at first job change	3.98	3.74	0.24	647
Year of experience at first job change|changes by 5th year	3.01	3.05	-0.04	514
Total number of years in sample	8.72	8.47	0.26**	984
Total number of weeks in sample	426.84	407.47	19.37***	984

Notes: NLSY97. The statistics are computed on a sample of 407 male and 577 female workers of all races and ethnicities. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table.

Table 16: Time-Invariant Sample Characteristics - Non-Missing Employer Dimension

	Males	Females	Diff.	Obs.
Age at labor market entry	24.08	24.16	-0.07	484
No more in education by labor market entry	0.67	0.65	0.02	484
Enrolled in school at labor market entry	0.16	0.17	-0.00	484
Bachelor degree by labor market entry	0.67	0.76	-0.09**	484
Master degree by age 26	0.06	0.10	-0.04	484
Prospective PhD graduate	0.03	0.00	0.03**	484
Married/cohabiting by labor market entry	0.24	0.38	-0.13***	484
Married/cohabiting by 3rd yr in labor market	0.46	0.59	-0.13***	484
Married/cohabiting by 5th yr in labor market	0.62	0.73	-0.11**	484
Married by 2015	0.66	0.73	-0.07	484
Has child by labor market entry	0.02	0.04	-0.03*	484
Has child by 3rd yr in labor market	0.10	0.12	-0.02	484
Has child by 5th yr in labor market	0.22	0.24	-0.02	484
Has child by 2015	0.52	0.61	-0.09**	484
Age at first child birth	28.50	28.14	0.36	275
Total number of jobs held	2.18	2.39	-0.21	484
Changes employer by 5th year in labor market	0.48	0.53	-0.04	484
Year of experience at first job change	3.82	3.42	0.40*	291
Year of experience at first job change|changes by 5th year	2.99	3.00	-0.01	246
Total number of years in sample	8.68	8.51	0.17	484
Total number of weeks in sample	427.97	411.66	16.31*	484

Notes: NLSY97. The statistics are computed on a sample of 215 male and 269 female non African-American and non Hispanic workers. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Employer dimension can be observed for all workers in the sample.

Table 17: Time-Invariant Sample Characteristics - No Children by 5th Year in Labor Market

	Males	Females	Diff.	Obs.
Age at labor market entry	24.04	24.06	-0.02	553
No more in education by labor market entry	0.63	0.60	0.03	553
Enrolled in school at labor market entry	0.16	0.18	-0.02	553
Bachelor degree by labor market entry	0.69	0.77	-0.08**	553
Master degree by age 26	0.05	0.10	-0.05**	553
Prospective PhD graduate	0.02	0.01	0.01	553
Married/cohabiting by labor market entry	0.15	0.29	-0.14***	553
Married/cohabiting by 3rd yr in labor market	0.36	0.50	-0.14***	553
Married/cohabiting by 5th yr in labor market	0.56	0.64	-0.08*	553
Married by 2015	0.61	0.63	-0.02	553
Has child by 2015	0.40	0.46	-0.06	553
Age at first child birth	29.95	29.68	0.27	239
Total number of jobs held	2.56	2.54	0.02	553
Changes employer by 5th year in labor market	0.52	0.53	-0.00	553
Year of experience at first job change	3.93	3.77	0.16	368
Year of experience at first job change|changes by 5th year	3.02	2.99	0.04	291
Total number of years in sample	8.74	8.48	0.26*	553
Total number of weeks in sample	426.77	408.36	18.41**	553

Notes: NLSY97. The statistics are computed on a sample of 246 male and 307 female non African-American and non Hispanic workers who do not have children by the fifth year in the labor market. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table.

Table 18: Time-Invariant Sample Characteristics - No Children by 2015

	Males	Females	Diff.	Obs.
Age at labor market entry	24.26	24.49	-0.22	314
No more in education by labor market entry	0.67	0.67	0.00	314
Enrolled in school at labor market entry	0.16	0.16	-0.00	314
Bachelor degree by labor market entry	0.69	0.80	-0.11**	314
Master degree by age 26	0.05	0.08	-0.03	314
Prospective PhD graduate	0.02	0.01	0.01	314
Married/cohabiting by labor market entry	0.11	0.22	-0.10**	314
Married/cohabiting by 3rd yr in labor market	0.24	0.36	-0.12**	314
Married/cohabiting by 5th yr in labor market	0.41	0.49	-0.08	314
Married by 2015	0.39	0.38	0.01	314
Total number of jobs held	2.51	2.54	-0.03	314
Changes employer by 5th year in labor market	0.50	0.52	-0.02	314
Year of experience at first job change	4.03	3.61	0.42	206
Year of experience at first job change|changes by 5th year	2.92	2.89	0.03	161
Total number of years in sample	8.32	8.08	0.25	314
Total number of weeks in sample	402.93	387.20	15.73	314

Notes: NLSY97. The statistics are computed on a sample of 148 male and 166 female non African-American and non Hispanic workers who do not have children by the fifth year in the labor market. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table.

Table 19: Time-Invariant Sample Characteristics - Not Married by 2015

	Males	Females	Diff.	Obs.
Age at labor market entry	24.10	24.27	-0.17	220
No more in education by labor market entry	0.71	0.63	0.08	220
Enrolled in school at labor market entry	0.11	0.16	-0.05	220
Bachelor degree by labor market entry	0.66	0.79	-0.14**	220
Master degree by age 26	0.03	0.09	-0.06*	220
Prospective PhD graduate	0.01	0.00	0.01	220
Cohabiting by labor market entry	0.03	0.15	-0.12***	220
Cohabiting by 3rd yr in labor market	0.12	0.27	-0.15***	220
Cohabiting by 5th yr in labor market	0.26	0.38	-0.12*	220
Has child by labor market entry	0.01	0.02	-0.01	220
Has child by 3rd yr in labor market	0.02	0.05	-0.03	220
Has child by 5th yr in labor market	0.03	0.07	-0.04	220
Has child by 2015	0.08	0.15	-0.07	220
Age at first child birth	28.75	27.22	1.53	26
Total number of jobs held	2.49	2.56	-0.07	220
Changes employer by 5th year in labor market	0.49	0.53	-0.03	220
Year of experience at first job change	4.06	3.62	0.45	143
Year of experience at first job change|changes by 5th year	2.96	2.88	0.08	113
Total number of years in sample	8.52	8.20	0.32	220
Total number of weeks in sample	412.31	392.17	20.14	220

Notes: NLSY97. The statistics are computed on a sample of 99 male and 121 female non African-American and non Hispanic workers who do not marry by 2015. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table.

Table 20: Time-Varying Sample Characteristics by Years in Labor Market - All Races and Ethnicities

	Males	Females	Diff.	Obs.
	(a) First Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	15.69	15.69	-0.00	984
Employer j provides unpaid parental leave	0.21	0.30	-0.08***	984
Employer j provides paid parental leave	0.33	0.49	-0.16***	984
Employer j provides child care	0.07	0.10	-0.03	984
Employer j provides flexible schedule	0.41	0.39	0.02	984
Employer j provides medical insurance	0.77	0.85	-0.07***	984
Employer j provides life insurance	0.58	0.63	-0.05*	984
Employer j provides dental care	0.71	0.77	-0.06**	984
Employer j provides stock ownership	0.21	0.19	0.02	984
Employer j number of employees	786.16	556.46	229.71	679
Average weekly hours worked at j	43.20	42.23	0.97*	984
Total number of weeks employed in t	47.86	48.73	-0.87*	984
	(b) Fifth Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	20.94	19.63	1.32*	984
Employer j provides unpaid parental leave	0.37	0.56	-0.18***	984
Employer j provides paid parental leave	0.50	0.55	-0.05	984
Employer j provides child care	0.09	0.11	-0.02	984
Employer j provides flexible schedule	0.50	0.43	0.07**	984
Employer j provides medical insurance	0.90	0.91	-0.01	984
Employer j provides life insurance	0.76	0.78	-0.03	984
Employer j provides dental care	0.83	0.87	-0.04	984
Employer j provides stock ownership	0.25	0.21	0.04	984
Employer j number of employees	746.88	749.64	-2.76	863
Average weekly hours worked at j	44.21	41.66	2.56***	984
Total number of weeks employed in t	49.32	47.32	2.00***	984
	(c) Last Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	26.83	22.83	4.00***	984
Employer j provides unpaid parental leave	0.50	0.63	-0.14***	984
Employer j provides paid parental leave	0.49	0.56	-0.08**	984
Employer j provides child care	0.12	0.12	-0.00	984
Employer j provides flexible schedule	0.54	0.46	0.08***	984
Employer j provides medical insurance	0.93	0.90	0.02	984
Employer j provides life insurance	0.79	0.79	0.01	984
Employer j provides dental care	0.84	0.86	-0.02	984
Employer j provides stock ownership	0.25	0.20	0.05*	984
Employer j number of employees	1002.58	778.39	224.19	699
Average weekly hours worked at j	44.10	40.99	3.11***	984
Total number of weeks employed in t	41.97	38.64	3.33***	984

Notes: NLSY97. The statistics are computed on a sample of 407 male and 577 female workers of all races and ethnicities. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Wages and hours information for all 984 workers in the sample is available for the first five-to-ten years since labor market entry. 120 male workers and 185 female workers in the sample have missing information regarding their first employer dimension, measured as number of employees. 39 male workers and 82 female workers have missing information regarding their fifth-year employer dimension. 110 male workers and 175 female workers have missing information regarding the dimension of their last employer.

Table 21: Time-Varying Characteristics by Years in Labor Market - Non-Missing Employer Dimension

	Males	Females	Diff.	Obs.
	(a) First Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	16.18	15.13	1.05	484
Employer j provides unpaid parental leave	0.19	0.29	-0.10**	484
Employer j provides paid parental leave	0.29	0.49	-0.20***	484
Employer j provides child care	0.07	0.10	-0.02	484
Employer j provides flexible schedule	0.41	0.41	0.00	484
Employer j provides medical insurance	0.74	0.83	-0.09**	484
Employer j provides life insurance	0.55	0.62	-0.07	484
Employer j provides dental care	0.67	0.74	-0.07*	484
Employer j provides stock ownership	0.24	0.20	0.04	484
Employer j number of employees	764.66	640.45	124.20	484
Average weekly hours worked at j	44.10	42.41	1.69**	484
Total number of weeks employed in t	47.64	49.07	-1.44**	484
	(b) Fifth Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	22.68	19.22	3.46***	484
Employer j provides unpaid parental leave	0.36	0.58	-0.22***	484
Employer j provides paid parental leave	0.45	0.55	-0.10**	484
Employer j provides child care	0.08	0.13	-0.05*	484
Employer j provides flexible schedule	0.49	0.44	0.05	484
Employer j provides medical insurance	0.93	0.93	-0.00	484
Employer j provides life insurance	0.76	0.82	-0.06*	484
Employer j provides dental care	0.84	0.87	-0.03	484
Employer j provides stock ownership	0.28	0.22	0.06	484
Employer j number of employees	936.42	746.55	189.87	484
Average weekly hours worked at j	45.28	42.47	2.81***	484
Total number of weeks employed in t	49.86	47.91	1.95**	484
	(c) Last Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	28.69	22.82	5.87***	484
Employer j provides unpaid parental leave	0.49	0.65	-0.16***	484
Employer j provides paid parental leave	0.48	0.56	-0.07	484
Employer j provides child care	0.11	0.11	-0.00	484
Employer j provides flexible schedule	0.56	0.45	0.12**	484
Employer j provides medical insurance	0.93	0.90	0.02	484
Employer j provides life insurance	0.76	0.79	-0.03	484
Employer j provides dental care	0.81	0.85	-0.04	484
Employer j provides stock ownership	0.24	0.19	0.05	484
Employer j number of employees	1194.20	591.36	602.84*	484
Average weekly hours worked at j	45.33	41.71	3.62***	484
Total number of weeks employed in t	42.18	38.38	3.79***	484

Notes: NLSY97. The statistics are computed on a sample of 215 male and 269 female non African-American and non Hispanic workers. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Wages and hours information for all 714 workers in the sample is available for the first five-to-ten years since labor market entry. Employer dimension can be observed for all workers in the sample.

Table 22: Time-Varying Characteristics by Years in Labor Market - No Children by 5th Year in Labor Market

	Males	Females	Diff.	Obs.
	(a) First Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	15.83	15.79	0.04	553
Employer j provides unpaid parental leave	0.22	0.26	-0.03	553
Employer j provides paid parental leave	0.34	0.50	-0.17***	553
Employer j provides child care	0.08	0.09	-0.01	553
Employer j provides flexible schedule	0.41	0.38	0.03	553
Employer j provides medical insurance	0.75	0.83	-0.08**	553
Employer j provides life insurance	0.57	0.63	-0.06	553
Employer j provides dental care	0.70	0.75	-0.05	553
Employer j provides stock ownership	0.22	0.18	0.04	553
Employer j number of employees	759.51	722.48	37.02	392
Average weekly hours worked at j	43.35	42.62	0.73	553
Total number of weeks employed in t	48.03	48.94	-0.91	553
	(b) Fifth Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	21.49	19.57	1.92**	553
Employer j provides unpaid parental leave	0.37	0.55	-0.18***	553
Employer j provides paid parental leave	0.51	0.58	-0.07*	553
Employer j provides child care	0.10	0.13	-0.04	553
Employer j provides flexible schedule	0.50	0.44	0.06	553
Employer j provides medical insurance	0.91	0.92	-0.01	553
Employer j provides life insurance	0.75	0.79	-0.04	553
Employer j provides dental care	0.85	0.88	-0.03	553
Employer j provides stock ownership	0.25	0.22	0.03	553
Employer j number of employees	799.78	774.90	24.88	478
Average weekly hours worked at j	44.15	42.65	1.50*	553
Total number of weeks employed in t	49.78	47.85	1.94***	553
	(c) Last Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	27.78	23.43	4.35***	553
Employer j provides unpaid parental leave	0.51	0.65	-0.14***	553
Employer j provides paid parental leave	0.49	0.57	-0.08*	553
Employer j provides child care	0.11	0.12	-0.01	553
Employer j provides flexible schedule	0.54	0.45	0.09**	553
Employer j provides medical insurance	0.93	0.90	0.03	553
Employer j provides life insurance	0.76	0.77	-0.01	553
Employer j provides dental care	0.83	0.85	-0.02	553
Employer j provides stock ownership	0.24	0.20	0.04	553
Employer j number of employees	1124.46	602.97	521.50	402
Average weekly hours worked at j	43.90	41.61	2.29**	553
Total number of weeks employed in t	41.90	38.40	3.50***	553

Notes: NLSY97. The statistics are computed on a sample of 246 male and 307 female non African-American and non Hispanic workers. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Wages and hours information for all 553 workers in the sample is available for the first five-to-ten years since labor market entry. 69 male workers and 92 female workers in the sample have missing information regarding their first employer dimension, measured as number of employees. 25 male workers and 50 female workers have missing information regarding their fifth-year employer dimension. 63 male workers and 88 female workers have missing information regarding the dimension of their last employer

Table 23: Time-Varying Characteristics by Years in Labor Market - No Children by 2015

	Males	Females	Diff.	Obs.
	(a) First Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	15.96	16.59	-0.63	314
Employer j provides unpaid parental leave	0.21	0.33	-0.12**	314
Employer j provides paid parental leave	0.35	0.53	-0.18***	314
Employer j provides child care	0.08	0.11	-0.03	314
Employer j provides flexible schedule	0.40	0.33	0.07	314
Employer j provides medical insurance	0.74	0.83	-0.08*	314
Employer j provides life insurance	0.58	0.61	-0.03	314
Employer j provides dental care	0.72	0.75	-0.04	314
Employer j provides stock ownership	0.22	0.18	0.04	314
Employer j number of employees	945.13	624.50	320.64	217
Average weekly hours worked at j	44.64	43.12	1.52	314
Total number of weeks employed in t	47.94	48.94	-1.00	314
	(b) Fifth Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	22.21	19.79	2.42*	314
Employer j provides unpaid parental leave	0.34	0.53	-0.19***	314
Employer j provides paid parental leave	0.46	0.59	-0.13**	314
Employer j provides child care	0.09	0.15	-0.06*	314
Employer j provides flexible schedule	0.49	0.41	0.08	314
Employer j provides medical insurance	0.92	0.91	0.01	314
Employer j provides life insurance	0.74	0.78	-0.05	314
Employer j provides dental care	0.87	0.87	-0.00	314
Employer j provides stock ownership	0.26	0.26	-0.00	314
Employer j number of employees	1045.04	811.13	233.91	271
Average weekly hours worked at j	45.02	42.88	2.14*	314
Total number of weeks employed in t	49.05	46.84	2.21*	314
	(c) Last Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	27.89	23.72	4.17**	314
Employer j provides unpaid parental leave	0.50	0.60	-0.10*	314
Employer j provides paid parental leave	0.49	0.59	-0.10*	314
Employer j provides child care	0.12	0.12	0.00	314
Employer j provides flexible schedule	0.55	0.46	0.09	314
Employer j provides medical insurance	0.94	0.90	0.04	314
Employer j provides life insurance	0.76	0.76	0.00	314
Employer j provides dental care	0.85	0.84	0.01	314
Employer j provides stock ownership	0.26	0.21	0.05	314
Employer j number of employees	1453.50	577.58	875.92	222
Average weekly hours worked at j	44.09	43.11	0.98	314
Total number of weeks employed in t	39.44	37.62	1.82	314

Notes: NLSY97. The statistics are computed on a sample of 148 male and 166 female non African-American and non Hispanic workers. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Wages and hours information for all 314 workers in the sample is available for the first five-to-ten years since labor market entry. 42 male workers and 55 female workers in the sample have missing information regarding their first employer dimension, measured as number of employees. 12 male workers and 31 female workers have missing information regarding their fifth-year employer dimension. 39 male workers and 53 female workers have missing information regarding the dimension of their last employer

Table 24: Time-Varying Characteristics by Years in Labor Market - Not Married by 2015

	Males	Females	Diff.	Obs.
	(a) First Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	15.25	16.59	-1.35	220
Employer j provides unpaid parental leave	0.19	0.37	-0.18***	220
Employer j provides paid parental leave	0.34	0.49	-0.14**	220
Employer j provides child care	0.05	0.08	-0.03	220
Employer j provides flexible schedule	0.36	0.32	0.04	220
Employer j provides medical insurance	0.69	0.83	-0.14**	220
Employer j provides life insurance	0.56	0.60	-0.05	220
Employer j provides dental care	0.68	0.74	-0.06	220
Employer j provides stock ownership	0.28	0.18	0.10*	220
Employer j number of employees	1085.53	688.96	396.57	151
Average weekly hours worked at j	44.25	43.23	1.02	220
Total number of weeks employed in t	48.05	48.07	-0.02	220
	(b) Fifth Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	21.17	19.69	1.48	220
Employer j provides unpaid parental leave	0.27	0.52	-0.25***	220
Employer j provides paid parental leave	0.46	0.61	-0.15**	220
Employer j provides child care	0.09	0.12	-0.03	220
Employer j provides flexible schedule	0.46	0.43	0.03	220
Employer j provides medical insurance	0.86	0.90	-0.04	220
Employer j provides life insurance	0.73	0.77	-0.04	220
Employer j provides dental care	0.81	0.85	-0.04	220
Employer j provides stock ownership	0.28	0.22	0.06	220
Employer j number of employees	1209.91	1044.82	165.09	186
Average weekly hours worked at j	44.51	42.62	1.89	220
Total number of weeks employed in t	48.92	48.38	0.54	220
	(c) Last Year in Sample			
Hourly rate of pay at j (in 2005 Dollars)	25.34	22.75	2.60	220
Employer j provides unpaid parental leave	0.40	0.55	-0.15**	220
Employer j provides paid parental leave	0.52	0.56	-0.05	220
Employer j provides child care	0.13	0.09	0.04	220
Employer j provides flexible schedule	0.53	0.45	0.08	220
Employer j provides medical insurance	0.92	0.85	0.07	220
Employer j provides life insurance	0.74	0.74	0.00	220
Employer j provides dental care	0.81	0.82	-0.01	220
Employer j provides stock ownership	0.24	0.23	0.01	220
Employer j number of employees	1597.27	679.20	918.06	154
Average weekly hours worked at j	43.43	42.51	0.92	220
Total number of weeks employed in t	40.03	37.71	2.32	220

Notes: NLSY97. The statistics are computed on a sample of 99 male and 121 female non African-American and non Hispanic workers. All workers in the sample graduate from college by age 25, are not unemployed or out of the labor market for one (or more than one) consecutive year(s) by the fifth year since labor market entry, and have non-missing information regarding all the variables in the table. Wages and hours information for all 220 workers in the sample is available for the first five-to-ten years since labor market entry. 25 male workers and 44 female workers in the sample have missing information regarding their first employer dimension, measured as number of employees. 9 male workers and 25 female workers have missing information regarding their fifth-year employer dimension. 24 male workers and 42 female workers have missing information regarding the dimension of their last employer

C Composition Adjusted Wages by Year of Experience

C.1 Calculating the Composition Adjusted Wages

I compute the composition adjusted mean wages shown in Figure 1 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.

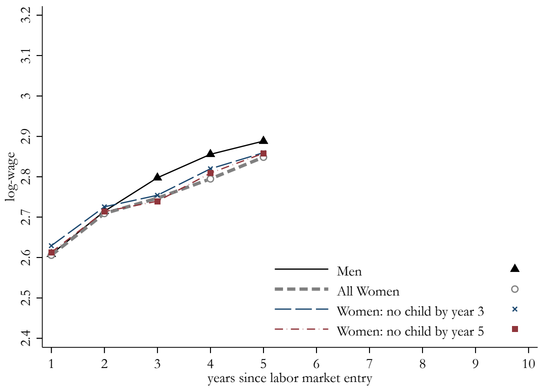
Subsequently, the cohort-gender specific average log-wages are weighted using the ratio between the total number of weeks worked by each cohort-gender group and the total number of weeks worked by workers of a given gender.[40] The gender-specific composition adjusted mean wage in a certain year of experience is the weighted average log-wage in that year of experience computed across different cohorts of labor market entrants.

C.2 Composition Adjusted Wages: Robustness Checks

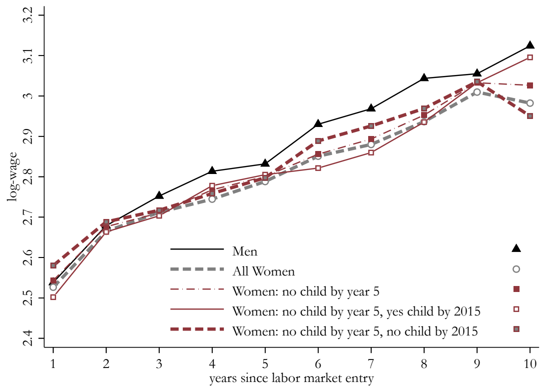
The figure below shows the evolution of the composition-adjusted mean wage by gender for workers of all races and ethnicities.

[40] 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 6: Composition Adjusted Mean Log-Wages - All Races, Women By Parental Status



(a) Enter Labor Market in 2000-2012



(b) Enter Labor Market in 2000-2007

Notes: National Longitudinal Survey of Youth, 1997. Workers of all races and ethnicities who graduate from college by age 25, who are continuously in employment by the fifth year on the labor market and who enter the labor market between 2000 and 2012 (panel (a)), or between 2000 and 2007 (panel (b)).

D Actual Experience, Potential Experience Work History Models

Table 25: Light and Ureta (1995) Experience Models Estimated Coefficients

	WH Males	WH Females	AE Males	AE Females	PE Males	PE Females
	b/se	b/se	b/se	b/se	b/se	b/se
WH = Fraction of Year worked 1 Years Ago	0.0961**	0.1478***				
	(0.0409)	(0.0319)				
WH = Fraction of Year worked 2 Years Ago	0.1012***	0.0558*				
	(0.0371)	(0.0291)				
WH = Fraction of Year worked 3 Years Ago	0.0759**	0.0950***				
	(0.0367)	(0.0287)				
WH = Fraction of Year worked 4 Years Ago	0.0571	0.0435				
	(0.0370)	(0.0289)				
WH = Fraction of Year worked 5 Years Ago	0.1227***	0.0678**				
	(0.0380)	(0.0300)				
WH = Fraction of Year worked 6 Years Ago	0.0548	0.0791**				
	(0.0399)	(0.0318)				
WH = Fraction of Year worked 7 Years Ago	0.1161***	0.0735**				
	(0.0424)	(0.0343)				
WH = Fraction of Year worked 8 Years Ago	0.0746	0.0676*				
	(0.0455)	(0.0384)				
WH = Fraction of Year worked 9 Years Ago	0.0589	0.0543				
	(0.0531)	(0.0449)				
Years of Tenure	0.0155	-0.0216	0.0149	-0.0172	0.0152	-0.0106
	(0.0207)	(0.0169)	(0.0196)	(0.0162)	(0.0190)	(0.0157)
Years of Tenure Squared	-0.0045*	0.0008	-0.0044*	0.0005	-0.0040*	-0.0000
	(0.0023)	(0.0019)	(0.0023)	(0.0019)	(0.0022)	(0.0018)
AE = Share of Time worked until present			0.0904***	0.0897***		
			(0.0183)	(0.0152)		
AE Squared			-0.0006	-0.0022		
			(0.0020)	(0.0017)		
PE = Years since labor market entry					0.0865***	0.0789***
					(0.0174)	(0.0143)
PE Squared					-0.0007	-0.0014
					(0.0018)	(0.0015)
Constant	2.3539***	2.4241***	2.3550***	2.4417***	2.3418***	2.4333***
	(0.0719)	(0.0496)	(0.0710)	(0.0488)	(0.0714)	(0.0488)
R^2	0.181	0.143	0.180	0.141	0.180	0.142
Observations	2698	3402	2698	3402	2698	3402
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

Notes: 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 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. The Table shows the coefficient estimates from the different models.

Table 26: Light and Ureta (1995) Experience Models - Predicted Log-Wages

	Males			Females		
	Year 2	Year 4	Year 6	Year 2	Year 4	Year 6
	(1)	(2)	(3)	(4)	(5)	(6)
	One Year of Tenure			One Year of Tenure		
Work History Model	2.683	2.860	3.040	2.691	2.841	2.953
Prediction Std. Err.	0.036	0.040	0.046	0.030	0.033	0.038
Actual Exp. Model	2.682	2.857	3.028	2.656	2.818	2.962
Prediction Std. Err.	0.029	0.032	0.037	0.024	0.027	0.032
Potential Exp. Model	2.676	2.843	3.004	2.652	2.799	2.935
Prediction Std. Err.	0.030	0.031	0.036	0.025	0.027	0.031

Notes: 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 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. The Table shows the predicted log-wages of male and female workers in selected years of experience and the standard error of the prediction.

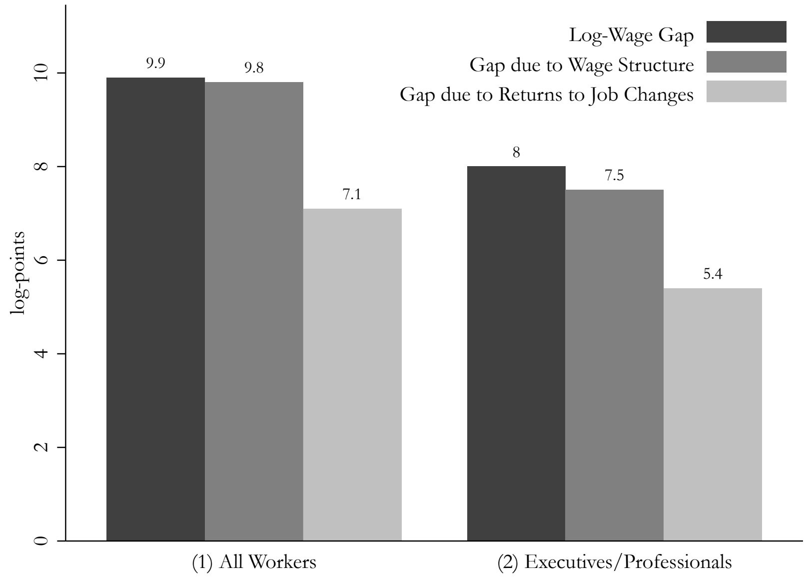
E Wage Gap Decomposition

Table 27: Wage Gap Decomposition - Results

	Total Gap	Wage Structure	Characteristics
	(a) All Workers		
Total	0.099	0.096	0.003
Job Changes	0.067	0.074	-0.007
Actual Experience	-0.076	-0.078	0.002
Tenure	0.141	0.137	0.004
Work Hours	-0.206	-0.202	-0.003
Firm Size	-0.028	-0.028	-0.000
Education	-0.140	-0.140	0.000
Career Interruptions	-0.023	-0.029	0.006
Unexplained Gap	0.364		
	(b) Executive and Professional Occupations		
Total	0.080	0.071	0.009
Job Changes	0.054	0.054	0.001
Actual Experience	-0.063	-0.069	0.006
Tenure	0.115	0.115	0.000
Work Hours	-0.827	-0.821	-0.005
Firm Size	0.005	0.004	0.001
Education	0.066	0.066	-0.000
Career Interruptions	-0.079	-0.086	0.007
Unexplained Gap	0.809		

Notes: National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic workers who are continuously in employment by the fifth year on the labor market and who enter the labor market between 2000 and 2011. The sample only includes individuals who never leave the labor market for more than one year in any of the first five years in the labor market. For each individual in the sample I only consider the first job in chronological order held in a certain year. The sample is restricted to workers with non-missing information for all variables in table 1. Panel (a) shows the wage gap among all workers in the sample, panel (b) shows the gap among workers who are mostly observed in Executive, Managerial and Professional specialty occupations, panel (c) shows the gap among workers who are mostly observed in the Information and Communication technology sector or in the Financial and Real Estate sector. The decomposition of the wage gap is performed after estimating gender-specific fixed effect regressions of workers' log-wage on the number of job changes until t, a quadratic term for the years of actual labor market experience, a quadratic term for the years of tenure at current employer, the logarithm of current work hours, the logarithm of current employer's number of employees, a dummy for whether a worker received their college degree by year t and the number of career interruptions (i.e. spells out of the labor market) until year t. The first column shows the raw gender pay gap between male and female workers, and the gap due to differences in observable characteristics and in their return. The second column indicates the portion of the gap due to differences in returns to observed characteristics, the last column indicates the portion of the gap due to average differences in observed characteristics between male and female workers in the sample. Given the use of the fixed effect estimator, the unexplained portion of the gender wage gap is unidentified.

Figure 7: Wage Gap Decomposition - Alternative Counterfactual



Notes: National Longitudinal Survey of Youth, 1997. Non African-American and non Hispanic workers who are continuously in employment by the fifth year on the labor market and who enter the labor market between 2000 and 2011. The sample only includes individuals who obtain a college degree by age 25 and never leave the labor market for more than one year in any of the first five years in the labor market. For each individual in the sample I only consider the first job in chronological order held in a certain year. Panel (1) shows the wage gap among all workers in the sample, panel (2) shows the gap among workers who are mostly observed in Executive, Managerial and Professional specialty occupations, panel (3) shows the gap among workers who are mostly observed in the Information and Communication technology sector or in the Financial and Real Estate sector. For each group, the first bar on the left (dark) shows the raw (log) wage gap between male and female workers, the second bar represents the wage gap due to different returns to observed characteristics, and the bar on the right shows the wage gap due to different returns to job changes. This figure shows the results of the decomposition using the predicted wage that a worker with the average male's characteristics would have obtained given women's returns to observed characteristics as counterfactual.

F Returns from Job Changes

Table 28: Returns to Job Change - All Coefficients

	Baseline with Controls Males	Baseline with Controls Females	Baseline with Year Dummies Males	Baseline with Year Dummies Females	Baseline with Year Trend Males	Baseline with Year Trend Females	Baseline with more Controls Males	Baseline with more Controls Females
	(3)	(4)	(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)	0.0859**	0.0817	0.0428	0.1178	0.0453	0.1025	0.0767**	0.0808
	(0.0433)	(0.0573)	(0.1987)	(0.1285)	(0.1955)	(0.1267)	(0.0378)	(0.0574)
AE(t-1) Squared	-0.0004	-0.0023	-0.0001	-0.0030	-0.0002	-0.0025	0.0008	-0.0025
	(0.0039)	(0.0058)	(0.0041)	(0.0061)	(0.0041)	(0.0060)	(0.0036)	(0.0059)
Change Job in t-1(**I**[Change(t-1)])	-0.2603	0.0005	-0.2818	0.0018	-0.2602	0.0018	-0.2575	-0.0056
	(0.1742)	(0.0756)	(0.1740)	(0.0750)	(0.1741)	(0.0762)	(0.1703)	(0.0895)
AE(t-1)***I**[Change(t-1)]	0.1306	0.0453	0.1337	0.0427	0.1287	0.0454	0.1375	0.0572
	(0.0870)	(0.0442)	(0.0848)	(0.0432)	(0.0864)	(0.0443)	(0.0866)	(0.0482)
AE(t-1)Sqr***I**[Change(t-1)]	-0.0096	-0.0063	-0.0097	-0.0060	-0.0094	-0.0063	-0.0108	-0.0078
	(0.0101)	(0.0058)	(0.0098)	(0.0056)	(0.0101)	(0.0058)	(0.0099)	(0.0060)
Bachelor Degree by t-2	0.0484	-0.0284	0.0157	-0.0240	0.0473	-0.0281	0.0326	-0.0296
	(0.0863)	(0.0465)	(0.0864)	(0.0445)	(0.0855)	(0.0464)	(0.0880)	(0.0465)
Enrolled in School in t-2	-0.0923	0.0669*	-0.0762	0.0667	-0.0937*	0.0666*	-0.0902*	0.0651*
	(0.0566)	(0.0395)	(0.0497)	(0.0408)	(0.0555)	(0.0393)	(0.0539)	(0.0341)
(Log) Weekly Hours in t-2	0.0398	-0.0450	0.0520	-0.0436	0.0406	-0.0460	0.0273	-0.0670
	(0.0698)	(0.0835)	(0.0735)	(0.0841)	(0.0704)	(0.0841)	(0.0667)	(0.0735)
Years of Tenure in t-2	-0.0271	-0.0220	-0.0349	-0.0253	-0.0254	-0.0230	-0.0264	-0.0248
	(0.0336)	(0.0374)	(0.0361)	(0.0396)	(0.0359)	(0.0389)	(0.0310)	(0.0400)
Tenure Sqr.	-0.0026	0.0015	-0.0016	0.0019	-0.0028	0.0016	-0.0032	0.0019
	(0.0039)	(0.0047)	(0.0042)	(0.0049)	(0.0041)	(0.0048)	(0.0039)	(0.0050)
Union bargained contract in t-2	-0.0643*	0.0031	-0.0745**	0.0105	-0.0641*	0.0032	-0.0404	-0.0007
	(0.0346)	(0.0285)	(0.0342)	(0.0291)	(0.0344)	(0.0286)	(0.0350)	(0.0278)
(Log) N. Employees at Employer in t-2	-0.0027	0.0037	-0.0039	0.0045	-0.0026	0.0038	-0.0030	-0.0022
	(0.0108)	(0.0108)	(0.0106)	(0.0112)	(0.0107)	(0.0109)	(0.0106)	(0.0109)
Parental Benefits available in t-2	0.0108	-0.0032	0.0085	-0.0048	0.0109	-0.0032	0.0044	-0.0129
	(0.0140)	(0.0175)	(0.0137)	(0.0176)	(0.0140)	(0.0175)	(0.0151)	(0.0196)
Flexible Schedule in t-2	0.0081	0.0594**	0.0151	0.0604**	0.0073	0.0595**	0.0002	0.0565**
	(0.0309)	(0.0262)	(0.0311)	(0.0263)	(0.0301)	(0.0262)	(0.0299)	(0.0231)
N. Gaps out of labor by t-2	-0.0205	0.0308	-0.0450	0.0337	-0.0267	0.0335	-0.0246	0.0321
	(0.0451)	(0.0299)	(0.0563)	(0.0341)	(0.0537)	(0.0337)	(0.0414)	(0.0293)
Unemployment Rate in t-2	-0.0099	-0.0037	-0.0048	0.0147	-0.0096	-0.0038	-0.0113	-0.0023
	(0.0092)	(0.0086)	(0.0363)	(0.0445)	(0.0091)	(0.0086)	(0.0093)	(0.0084)
Medical Insurance in t-2							0.0498	-0.1005
							(0.0590)	(0.1050)
Life Insurance in t-2							-0.0265	-0.0215
							(0.0446)	(0.0553)
Dental Care in t-2							-0.0984	0.1678*
							(0.0834)	(0.0952)
Retirement Plan in t-2							0.0941*	0.0426
							(0.0480)	(0.0602)
Stock Ownership in t-2							0.0501	0.0303
							(0.0392)	(0.0381)
Adjusted R^2	0.110	0.092	0.117	0.093	0.109	0.092	0.123	0.107
N	1790	2188	1790	2188	1790	2188	1790	2188
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	N	N
Occupation $t-2$	N	N	N	N	N	N	Y	Y
Industry $t-2$	N	N	N	N	N	N	Y	Y
Additional Contr. $t-2$	N	N	N	N	N	N	Y	Y

Notes: 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. All models 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 $t-2$ employer, 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 $t-2$. Models in columns (7) and (8) also include 1-digit occupation and 1-digit industry dummies, and controls for whether $t-2$ employer offered respectively, medical insurance, life insurance, dental care, a retirement plan, and stock ownership to employees. The table shows the coefficients of the interactions between the reason-specific job-change dummies and the linear term in the actual experience polynomial.

Table 29: Returns to Job Change - By Reason Driving 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)	0.0852**	0.0767	0.0862	0.1106	0.0967	0.0945	0.0771**	0.0759
	(0.0423)	(0.0581)	(0.1954)	(0.1314)	(0.1926)	(0.1299)	(0.0372)	(0.0586)
AE(t-1) Squared	-0.0001	-0.0019	-0.0001	-0.0026	-0.0002	-0.0020	0.0010	-0.0021
	(0.0039)	(0.0059)	(0.0040)	(0.0062)	(0.0040)	(0.0061)	(0.0036)	(0.0060)
I[Change(t-1)]*Job *Destroyed*(D(t-2))	0.0107	0.1612*	-0.0235	0.1583	0.0115	0.1607*	0.0438	0.2046*
	(0.1330)	(0.0969)	(0.1423)	(0.0968)	(0.1348)	(0.0956)	(0.1253)	(0.1123)
I[Change(t-1)]*Job Shopping(S(t-2))	-0.2865**	-0.0249	-0.2917**	-0.0100	-0.2857**	-0.0240	-0.2597*	-0.0245
	(0.1409)	(0.0934)	(0.1422)	(0.0939)	(0.1408)	(0.0927)	(0.1468)	(0.1252)
I[Change(t-1)]*Family Constr.(FC(t-2))	0.1292	-0.1234	-4.6792	-0.0822	0.2588	-0.1205	-3.0147	-0.3714
	(3.3935)	(0.1678)	(6.2138)	(0.1868)	(4.0513)	(0.1701)	(5.1102)	(0.2737)
I[Change(t-1)]*Dislikes Job(DJ(t-2))	-0.5804	0.3614*	-0.7191	0.3821*	-0.5751	0.3602*	-0.7606	0.3711
	(0.9443)	(0.2170)	(0.9604)	(0.2089)	(0.9393)	(0.2166)	(1.0519)	(0.2668)
I[Change(t-1)]*Other Motives(O(t-2))	-0.8582	-0.1671	-0.8319	-0.1721	-0.8598	-0.1665	-0.8422	-0.1658
	(0.6790)	(0.2226)	(0.6199)	(0.2239)	(0.6788)	(0.2229)	(0.6490)	(0.2139)
I[Change(t-1)]*Mobility Constr.(MC(t-2))	0.4755	0.1174	0.3997	0.1253	0.4799	0.1207	0.2710	0.1023
	(0.6871)	(0.2713)	(0.6174)	(0.2751)	(0.6888)	(0.2746)	(0.6464)	(0.2511)
AE(t-1)***I**[Change(t-1)]*D(t-2)	0.0521	-0.0454*	0.0579	-0.0445*	0.0524	-0.0447*	0.0525	-0.0494*
	(0.0462)	(0.0236)	(0.0463)	(0.0227)	(0.0453)	(0.0229)	(0.0484)	(0.0259)
AE(t-1)***I**[Change(t-1)]*S(t-2)	0.1846**	0.0607	0.1818**	0.0539	0.1843**	0.0607	0.1739**	0.0662
	(0.0845)	(0.0589)	(0.0844)	(0.0583)	(0.0837)	(0.0589)	(0.0837)	(0.0605)
AE(t-1)***I**[Change(t-1)]*FC(t-2)	-0.0335	0.3111***	1.0149	0.3036***	-0.0614	0.3122***	0.6486	0.4318***
	(0.7387)	(0.1108)	(1.3509)	(0.1122)	(0.8789)	(0.1102)	(1.1089)	(0.1580)
AE(t-1)***I**[Change(t-1)]*DJ(t-2)	0.1971	-0.2229	0.2830	-0.2731	0.1938	-0.2216	0.3311	-0.2405
	(0.8731)	(0.1863)	(0.8670)	(0.1867)	(0.8617)	(0.1864)	(0.9348)	(0.2276)
AE(t-1)***I**[Change(t-1)]*O(t-2)	0.3454	0.0812	0.3318	0.0807	0.3466	0.0816	0.3476	0.0861
	(0.2986)	(0.1130)	(0.2739)	(0.1122)	(0.3002)	(0.1134)	(0.2848)	(0.1057)
AE(t-1)***I**[Change(t-1)]*MC(t-2)	-0.0192	0.0650	-0.0028	0.0512	-0.0207	0.0633	0.1113	0.0804
	(0.3274)	(0.1526)	(0.3029)	(0.1527)	(0.3292)	(0.1547)	(0.3101)	(0.1447)
AE(t-1)Sqr.***I**[Change(t-1)]*S(t-2)	-0.0172	-0.0074	-0.0166	-0.0071	-0.0172	-0.0074	-0.0160	-0.0079
	(0.0109)	(0.0086)	(0.0108)	(0.0085)	(0.0108)	(0.0086)	(0.0106)	(0.0081)
AE(t-1)Sqr.***I**[Change(t-1)]*FC(t-2)	0.0000	-0.0570***	0.0000	-0.0571***	0.0000	-0.0572***	0.0000	-0.0682***
	(.)	(0.0157)	(.)	(0.0156)	(.)	(0.0158)	(.)	(0.0194)
AE(t-1)Sqr.***I**[Change(t-1)]*DJ(t-2)	-0.0237	0.0419	-0.0352	0.0528	-0.0231	0.0418	-0.0456	0.0472
	(0.1549)	(0.0323)	(0.1520)	(0.0324)	(0.1529)	(0.0323)	(0.1629)	(0.0392)
AE(t-1)Sqr.***I**[Change(t-1)]*O(t-2)	-0.0297	-0.0062	-0.0283	-0.0060	-0.0298	-0.0062	-0.0308	-0.0069
	(0.0302)	(0.0125)	(0.0279)	(0.0124)	(0.0304)	(0.0126)	(0.0286)	(0.0117)
AE(t-1)Sqr.***I**[Change(t-1)]*MC(t-2)	-0.0031	-0.0183	-0.0039	-0.0161	-0.0030	-0.0180	-0.0194	-0.0202
	(0.0353)	(0.0196)	(0.0331)	(0.0194)	(0.0354)	(0.0199)	(0.0334)	(0.0193)
Adjusted R^2	0.120	0.093	0.126	0.094	0.120	0.092	0.135	0.107
N	1790	2188	1790	2188	1790	2188	1790	2188
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	N	N
Occupation $t-2$	N	N	N	N	N	N	Y	Y
Industry $t-2$	N	N	N	N	N	N	Y	Y
Additional Contr. $t-2$	N	N	N	N	N	N	Y	Y

Notes: 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. All models 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 $t-2$ employer, 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 $t-2$. Models in columns (7) and (8) also include 1-digit occupation and 1-digit industry dummies, and controls for whether $t-2$ employer offered respectively, medical insurance, life insurance, dental care, a retirement plan, and stock ownership to employees. The table shows the coefficients of the interactions between the reason-specific job-change dummies and the linear term in the actual experience polynomial.

G 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 30 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 $z_{ijt}^k = Z_{ijt}^k$ and Z^k is a continuous real valued variable. Then the semi-elasticity of p_{ijt} with respect to Z_{ijt}^k is

$$
\begin{aligned}
\zeta_{it}^{Z^k} &= \frac{\partial p_{ijt}}{\partial Z_{ijt}^k}\frac{1}{p_{ijt}} \\
&= \xi_k \frac{1}{1+\exp\{z_{ijt}'\xi+\nu_i\}} \\
&= \xi_k \left(1-p_{ijt}\right) \qquad (29)
\end{aligned}
$$

Implying that mean semi-elasticities can be consistently estimated using the same estimator as above. Finally, suppose that z_{ijt}^k is a dummy variable. Then, letting $p_{ijt}^1 = \Pr[y_{ijt}=1|z_{ijt}^1,..., z_{ijt}^k = 1,..., z_{ijt}^K, \nu_i]$ and $p_{ijt}^0 = \Pr\left[y_{ijt}=1|z_{ijt}^1,..., z_{ijt}^k = 0,..., z_{ijt}^K, \nu_i\right]$ the percentage change in p_{ijt} when z_{ijt}^k goes from 0 to 1 can be written as

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

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 30: Conditional Logit Models of Job Quit

	Males	Females
I[Job($t+1$) $\neq$ Job]		
Log-Hourly Wage in 2005 USD	-0.4447***	-0.7524***
	(0.1563)	(0.1820)
AE(t)	0.1327	0.0520
	(0.1773)	(0.1634)
AE(t) Squared	-0.0364*	-0.0377**
	(0.0197)	(0.0184)
Years of Tenure(t)	0.1930	0.4068**
	(0.1810)	(0.1667)
Years of Tenure(t) Squared	0.0187	-0.0005
	(0.0233)	(0.0221)
Log-Weekly Hours Worked	-1.2540***	-0.1118
	(0.4319)	(0.2515)
I[Union Bargained Contract]	0.1568	-0.3925
	(0.2897)	(0.2517)
I[Parental Benefits Available at j]	-0.3198***	-0.3112***
	(0.1184)	(0.1196)
I[Flexible Schedule Available at j]	-0.6078***	-0.8404***
	(0.1997)	(0.1916)
Log-Number of Employees at Employer j	-0.1614**	-0.0705
	(0.0633)	(0.0557)
First Child Born by t	-0.3546	-0.6436**
	(0.3723)	(0.3213)
Married by t	-0.7155**	-0.5595**
	(0.3320)	(0.2636)
Bachelor Degree by t	0.5791	0.6005*
	(0.3644)	(0.3586)
Enrolled in Formal Education Program at t	-0.1299	-0.5490**
	(0.2754)	(0.2538)
Total Number of Spells out of Lab.Force by t	-0.4273***	-0.4733***
	(0.1276)	(0.0971)
N	1479	1751
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.

H Model Estimation

E1. functional forms for $f(w^*, \mathbf{a}^*|.)$ and $\bar{F}_u(u|.)$

I show here how to find functional the functional forms for $f(w^*, \mathbf{a}^*|.)$ and $\bar{F}_u(u|.)$ needed to estimate the model.

First, the functional form for $f(w^*, \mathbf{a}^*|.)$ can be found as follows. Let $\mu_0^w + \mu_1^w b + \sum_{occ=1}^3 \varphi_{occ}^w \text{car}_{occ} + \sum_{ind=1}^3 \varphi_{ind}^w \text{car}_{ind} = \mu^w(X)$, where $X = \{b, \text{car}_{occ}, \text{car}_{ind}\}$. Notice that

$$f(w^*, \mathbf{a}^*|.) = f(w^*|\mathbf{a}^*, .)P(\mathbf{a}^*|.) = f(w^*|\mathbf{a}^*, .)\prod_{k=1}^{K} P(a_k^*|.) \tag{31}$$

To find an expression for $f(w^*|\mathbf{a}^*, .)$, notice that

$$\begin{aligned} F(w^*|.) &= P(\mu^w(X) + \rho'\mathbf{a} + \sigma_w \varepsilon_w \leq w^*) \\ &= P\left(\varepsilon_w \leq \frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right) \\ &= \Phi\left(\frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right) \end{aligned} \tag{32}$$

So that

$$f(w^*|.) = \frac{1}{\sigma_w}\phi\left(\frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right) \tag{33}$$

Where $\Phi(.)$ and $\phi(.)$ denote, respectively, the standard normal CDF and PDF.

Regarding $P(\mathbf{a}^*|.)$, let $\mu_0^{a_k} + \mu_1^{a_k} b + \sum_{occ=1}^3 \varphi_{occ}^{a_k} \text{car}_{occ} + \sum_{ind=1}^3 \varphi_{ind}^{a_k} \text{car}_{ind} = \mu^{a_k}(X)$, where $X = \{b, \text{car}_{occ}, \text{car}_{ind}\}$. Notice that, for every k, a_k takes value 1 if an employer offers amenity a_k and 0 otherwise. Hence,

$$P(a_k^*|.) = p^{a_k^*}(1-p)^{1-a_k^*} \tag{34}$$

Where

$$\begin{aligned} p &= P(\mu^{a_k}(X) + \varepsilon_{a_k} > 0) \\ &= P(\varepsilon_{a_k} > -\mu^{a_k}(X)) \\ &= 1 - \Phi(-\mu^{a_k}(X)) = \Phi(\mu^{a_k}(X)) \end{aligned} \tag{35}$$

So that, for each amenity a_k

$$\begin{aligned} P(a_k^*|.) &= \Phi(\mu^{a_k}(X))^{a_k^*}(1 - \Phi(\mu^{a_k}(X)))^{1-a_k^*} \\ &= \Phi\left(\mu^{a_k}(X)(-1)^{(1-a_k^*)}\right) \end{aligned} \tag{36}$$

Substituting (33) and (36) in (31)

$$f(w^*, \mathbf{a}^*|.) = \frac{1}{\sigma_w}\phi\left(\frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right)\prod_{k=1}^{K}\Phi\left(\mu^{a_k}(X)(-1)^{(1-a_k^*)}\right) \tag{37}$$

The functional form for $\bar{F}_u(u|.)$ can be found as follows. First, notice that

$$\bar{F}_u(u|.) = \sum_{\mathbf{a}^*\in\{0,1\}^K} \bar{F}(u|\mathbf{a}^*, .)P(\mathbf{a}^*|.) \tag{38}$$

Where

$$\begin{aligned}
\bar{F}(u|\mathbf{a}^*, .) &= 1 - P(w^* + \delta'\mathbf{a}^* \leq u|.) \\
&= 1 - P(\mu^w(X) + \rho'\mathbf{a}^* + \sigma_w\varepsilon_w + \delta'\mathbf{a}^* \leq u) \\
&= 1 - P\left(\varepsilon_w \leq \frac{-(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right) \\
&= 1 - \Phi\left(-\frac{(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right) \\
&= \Phi\left(\frac{(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right)
\end{aligned} \tag{39}$$

Substituting (39) and (36) into (38)

$$\bar{F}_u(u|.) = \sum_{\mathbf{a}^*\in\{0,1\}^K} \Phi\left(\frac{(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right)\prod_{k=1}^{K}\Phi\left(\mu^{a_k}(X)(-1)^{(1-a_k^*)}\right) \tag{40}$$

E2. The Bonhomme & Jolivet (2009) Iterative Estimation procedure - No Unobserved Heterogeneity

I explain here the iterative estimation procedure proposed by Bonhomme & Jolivet (2009). I implement the procedure separately for male and female workers.

For every $t \in [0, T]$, a worker's contribution to the likelihood in $(t + 1)$ in equation (19) can be rewritten as

$$l_{t+1}(\theta, \lambda, \delta) = l_{1,t+1}(\theta) \times l_{2,t+1}(\theta, \lambda, \delta) \times l_{3,t+1}(\theta, \lambda, \delta) \tag{41}$$

Where

$$l_{1,t+1}(\theta) = f(w_{t+1}, a_{t+1}; \theta)^{uj_t} \tag{42}$$

$$l_{2,t+1}(\theta, \lambda, \delta) = [1 - \lambda_1 \bar{F}(w_t + \delta' \mathbf{a}_t; \theta) - \lambda_2 - q]^{s_t} [\lambda_1 \bar{F}(w_t + \delta' \mathbf{a}_t; \theta) + \lambda_2]^{jj_t} \tag{43}$$

$$l_{3,t+1}(\theta, \lambda, \delta) = q^{ju_t} [1 - \lambda_0]^{uu_t} \lambda_0^{uj_t} \left[\frac{(\mathbf{1}\{w_{t+1} + \delta' \mathbf{a}_{t+1} > w_t + \delta' \mathbf{a}_t\} + \lambda_2) f(w_{t+1}, a_{t+1}; \theta)}{\lambda_1 \bar{F}(w_t + \delta' \mathbf{a}_t; \theta) + \lambda_2} \right]^{jj_t} \tag{44}$$

The model parameters can be estimated as follows.

First, the transitions out of unemployment identify θ, as unemployed workers accept any offer they receive. Hence, the parameter vector describing the features of the job offers distribution is estimated as

$$\hat{\theta} = \text{argmax}_\theta \log L_1 = \text{argmax}_\theta \sum_{i=1}^{N} \sum_{t=t_0}^{T} \log l_{1,t+1} \tag{45}$$

Second, taking $\hat{\theta}$, I guess an initial value $\tilde{\delta}$ for workers' preferences for amenities, and estimate

$$\begin{aligned} \hat{\lambda}^1 &= \text{argmax}_\lambda \log L_2 + \log L_3 = \\ &= \text{argmax}_\lambda \sum_{i=1}^{N} \sum_{t=t_0}^{T} \log l_{2,t+1}(\hat{\theta}, \lambda, \tilde{\delta}) + \log l_{3,t+1}(\hat{\theta}, \lambda, \tilde{\delta}) \end{aligned} \tag{46}$$

Finally, taking $\hat{\theta}$ and $\hat{\lambda}^1$ as given, I use the marginal likelihood of staying at current job or switching job to find an estimate for workers' preferences $\hat{\delta}^1$

$$\hat{\delta}^1 = \text{argmax}_\delta \log L_2 = \text{argmax}_\delta \sum_{i=1}^{N} \sum_{t=t_0}^{T} \log l_{2,t+1}(\hat{\theta}, \hat{\lambda}^1, \delta) \tag{47}$$

I iterate the last two step until convergence. In the data I use, approximately 10 iterations are required for the estimation to converge, for both male and female workers. The likelihood function I estimate, includes all $t \in (1, T)$.

E3. Structural Parameter Estimates

Table 31: Estimated Marginal Willingness to Pay for Amenities

	Estimated Preferences Parameters $\hat{\delta_k}$		The Wage Value of Amenities $e^{-\delta_k}$	
	Males	Females	Males	Females
Long Hours	0.606	0.400	0.545	0.670
LR Test p-Value	[0.049]	[1.000]		
Childcare	0.656	1.140	0.519	0.726
LR Test p-Value	[1.000]	[1.000]		

Notes: National Longitudinal Survey of Youth, 1997. 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.

Table 32: 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.	0.403	-0.128	0.254	0.495	0.606	-0.098	-0.286	-0.437
Asy.Std.Err.	(1.694)	(0.391)	(0.294)	(0.415)	(0.432)	(0.314)	(0.518)	(0.370)
LR Test p-Value	[0.410]	[0.260]	[0.010]	[1.000]	[0.090]	[0.710]	[1.000]	[0.580]
				Males				
Coeff.	1.946	-0.526	0.310	0.614	0.394	-0.214	0.682	0.060
Asy.Std.Err.	(2.741)	(0.622)	(0.425)	(0.452)	(0.339)	(0.482)	(0.685)	(0.371)
LR Test p-Value	[1.000]	[1.000]	[0.000]	[0.001]	[0.008]	[1.000]	[0.093]	[1.000]

National Longitudinal Survey of Youth, 1997.

Table 33: 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.	-2.693	0.432	-0.283	0.283	-0.894	-0.044	1.130	-0.073
Asy.Std.Err.	(1.950)	(0.450)	(0.347)	(0.383)	(0.860)	(0.370)	(0.549)	(0.349)
LR Test p-Value	[0.100	[0.550]	[1.000]	[0.120]	[0.010]	[0.780]	[0.030]	[0.580]
				Males				
Coeff.	-2.149	0.422	0.478	0.173	0.309	-0.873	-0.991	-0.533
Asy.Std.Err.	(3.544)	(0.800)	(0.497)	(0.546)	(0.454)	(0.511)	(0.828)	(0.442)
LR Test p-Value	[0.325]	[0.001]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]

National Longitudinal Survey of Youth, 1997.

Table 34: 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.	2.429	-0.387	0.449	0.536	0.182	-0.741	-0.552	-0.801
Asy.Std.Err.	(2.049)	(0.471)	(0.303)	(0.503)	(0.409)	(0.340)	(0.473)	(0.352)
LR Test p-Value	[0.120]	[0.220]	[0.340]	[0.060]	[0.860]	[1.000]	[0.090]	[1.000]
				Males				
Coeff.	-1.106	0.306	0.347	0.24	-0.446	-0.515	0.596	0.037
Asy.Std.Err.	(2.729)	(0.611)	(0.434)	(0.487)	(0.355)	(0.408)	(0.695)	(0.369)
LR Test p-Value	[1.000]	[1.000]	[1.000]	[1.000]	[0.084]	[1.000]	[1.000]	[0.351]

National Longitudinal Survey of Youth, 1997.

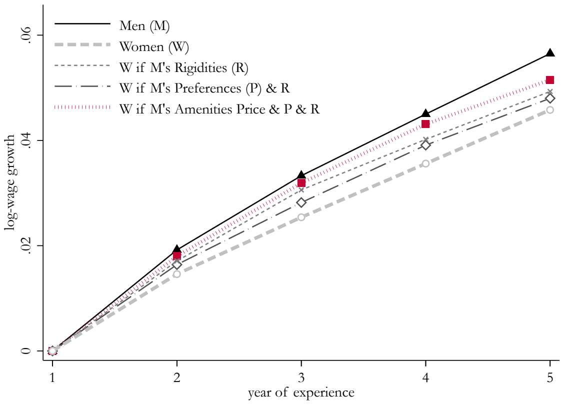
Table 35: Estimated Childcare Parameters

	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.	-1.264	0.027	-0.135	0.144	-0.374	0.122	0.311	0.094
Asy.Std.Err.	(1.932)	(0.459)	(0.359)	(0.473)	(0.663)	(0.368)	(0.632)	(0.444)
LR Test p-Value	[0.420]	[1.000]	[1.000]	[1.000]	[1.000]	[0.240]	[0.690]	[0.520]
				Males				
Coeff.	1.822	-0.834	-0.197	0.546	-5.043	0.214	0.389	0.804
Asy.Std.Err.	(3.619)	(0.863)	(0.764)	(0.584)		(0.992)	(1.262)	(0.686)
LR Test p-Value	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.001]

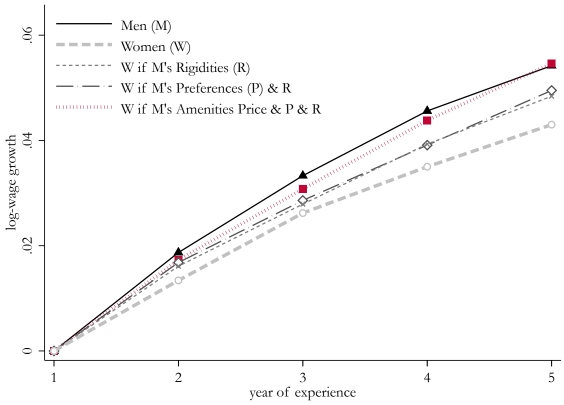
National Longitudinal Survey of Youth, 1997.

E4. Counterfactual Women's Wage Growth Profiles By Career

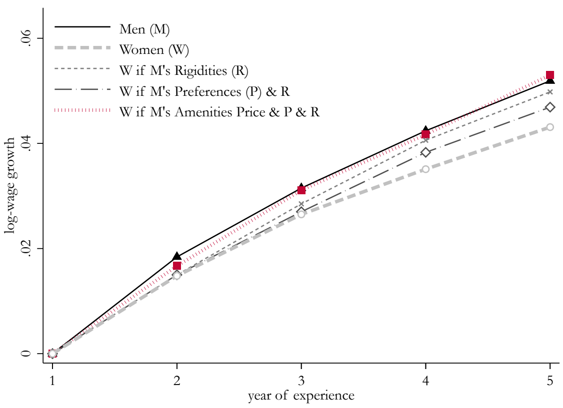
Figure 8: Predicted Log-Wage Profiles - Administrative, Education, Health, and Social Services Sector



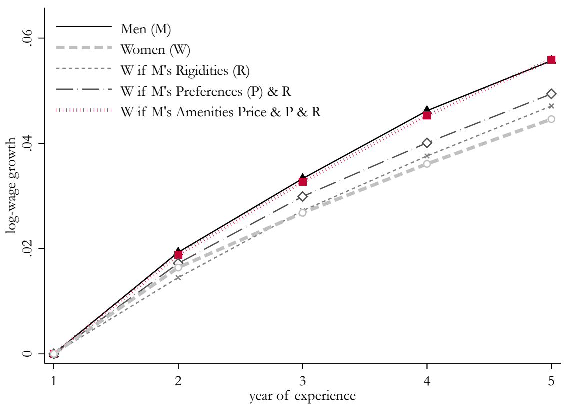
(a) Administratives



(c) Executives



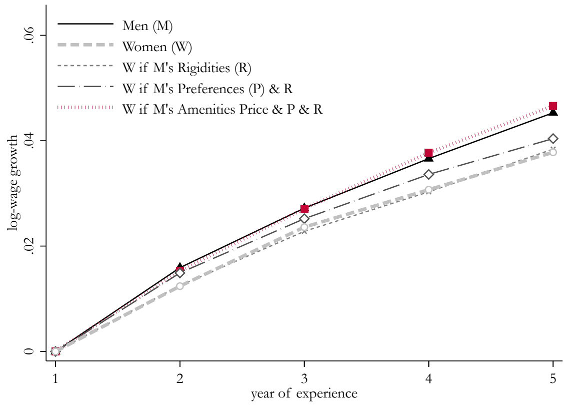
(d) Professionals



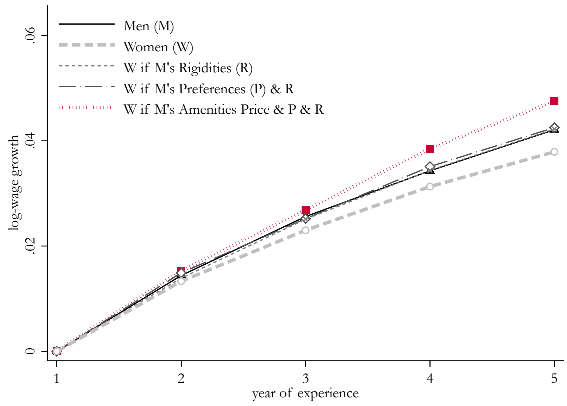
(b) Others

Notes: National Longitudinal Survey of Youth, 1997. Model predicted wage growth path for the career-specific representative woman in and counterfactual wage paths.

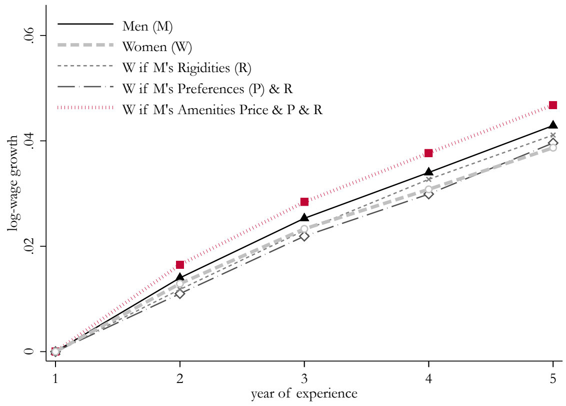
Figure 9: Predicted Log-Wage Profiles - Finance, Information, Real Estate



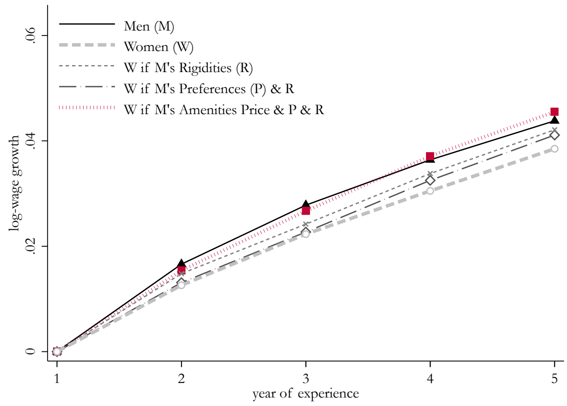
(a) Administratives



(b) Executives



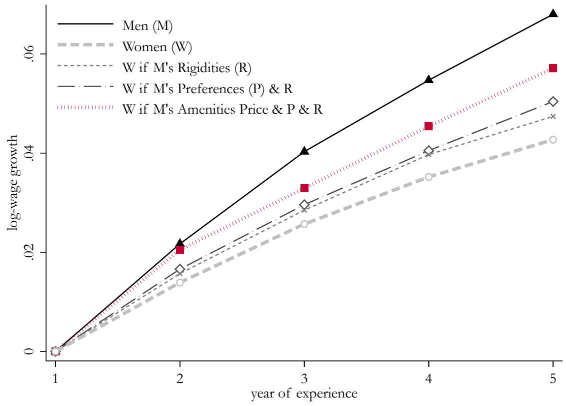
(c) Professionals



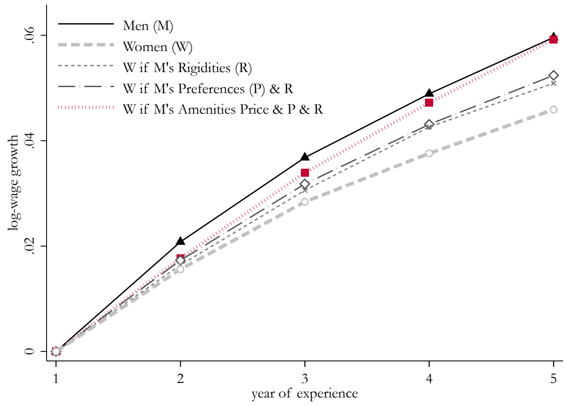
(d) Others

Notes: National Longitudinal Survey of Youth, 1997. Model predicted wage growth path for the career-specific representative woman in and counterfactual wage paths.

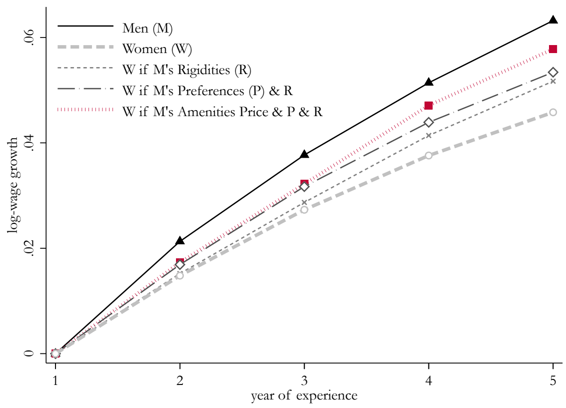
Figure 10: Predicted Log-Wage Profiles - Trade Sector



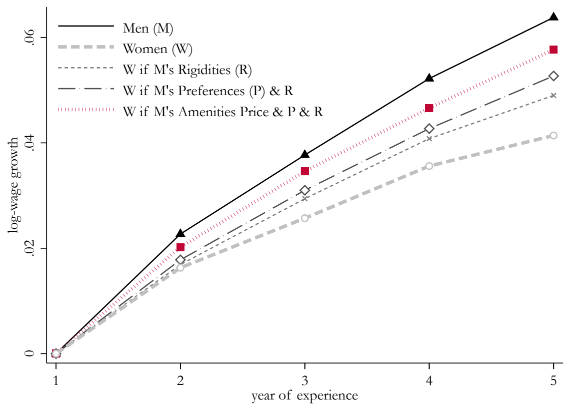
(a) Administratives



(c) Executives



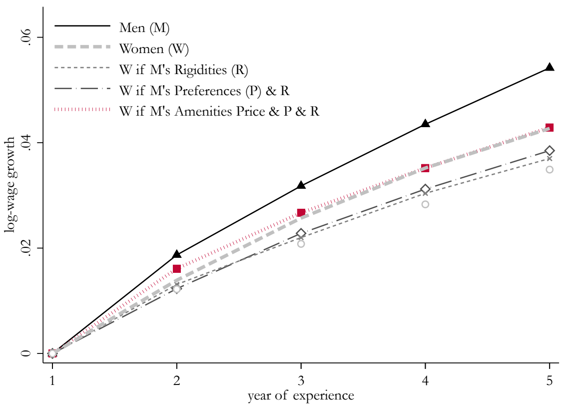
(d) Professionals



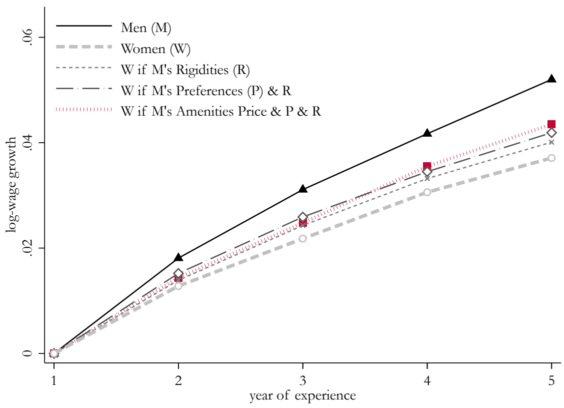
(b) Others

Notes: National Longitudinal Survey of Youth, 1997. Model predicted wage growth path for the career-specific representative woman in and counterfactual wage paths.

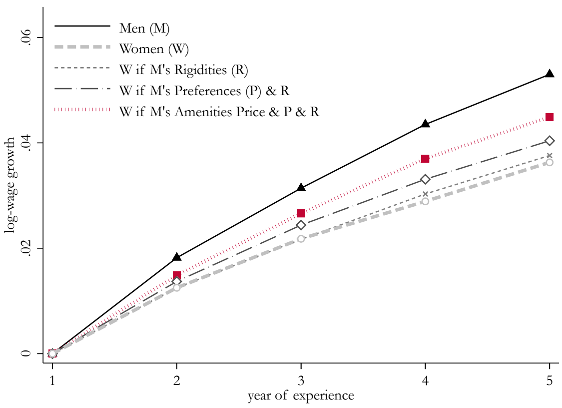
Figure 11: Predicted Log-Wage Profiles - Other Sectors



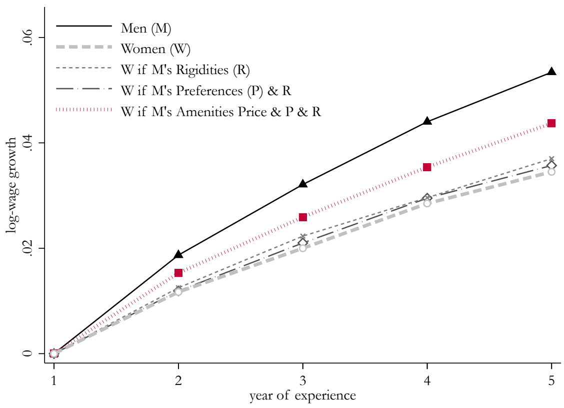
(a) Administratives



(b) Executives



(c) Professionals



(d) Others

Notes: National Longitudinal Survey of Youth, 1997. Model predicted wage growth path for the career-specific representative woman in and counterfactual wage paths.

8 E5: Decomposing the Expected Utility from Job Offers

In this section, I use the model estimates to predict the steady state distribution of utility in job offers, and decompose the female-to-male gap in the expected utility from job offers into different components. Given workers' *ability* (b) and given the occupation and industry classes defining workers' career, the expected utility from a job offer for a worker of gender $g = \{f, m\}$ is

$$
\begin{aligned}
E(u|g, b, \text{car}_{occ}, \text{car}_{ind}) &= E(w + \delta' \mathbf{a}|g, b, \text{car}_{occ}, \text{car}_{ind}) \\
&= \mu_0^g + \mu_1^g b + \sum_{occ=1}^{3} \varphi_{occ}^{g,w} \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,w} \text{car}_{ind} + \\
&+ \sum_{k=1}^{4} \rho_k^g \mathrm{P}(a_k^{of} = 1|g, b, \text{car}_{occ}, \text{car}_{ind}) + \sum_{k=1}^{4} \delta_k^g \mathrm{P}(a_k^{of} = 1|g, b, \text{car}_{occ}, \text{car}_{ind}) \\
&= \mu_0^g + \mu_1^g b + \sum_{occ=1}^{3} \varphi_{occ}^{g,w} \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,w} \text{car}_{ind} + \\
&+ \sum_{k=1}^{4} \rho_k^g \Phi \left(\mu_0^{g,a_k} + \mu_1^{g,a_k} b + \sum_{occ=1}^{3} \varphi_{occ}^{g,a_k} \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,a_k} \text{car}_{ind} \right) + \\
&+ \sum_{k=1}^{4} \delta_k^g \Phi \left(\mu_0^{g,a_k} + \mu_1^{g,a_k} b + \sum_{occ=1}^{3} \varphi_{occ}^{g,a_k} \text{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{g,a_k} \text{car}_{ind} \right) \qquad (48)
\end{aligned}
$$

The estimated difference in the utility that comparable female and male workers expect to receive from job offers is

$$
\begin{aligned}
\hat{E}(u|f,.) - \hat{E}(u|m,.) = &\left[(\hat{\mu}_0^f + \hat{\varphi}_j^{f,w} + \hat{\varphi}_\tau^{f,w}) - (\hat{\mu}_0^m + \hat{\varphi}_j^{m,w} + \hat{\varphi}_\tau^{m,w}) \right] + (\hat{\mu}_1^f - \hat{\mu}_1^m) b + \\
&+ \sum_{k=1}^{4} \hat{\rho}_k^f \left[\hat{\Phi}^f(.) - \hat{\Phi}^m(.) \right] + \sum_{k=1}^{4} \hat{\Phi}^m(.) \left(\hat{\rho}_k^f - \hat{\rho}_k^m \right) \\
&+ \sum_{k=1}^{4} \hat{\delta}_k^f \left[\hat{\Phi}^f(.) - \hat{\Phi}^m(.) \right] + \sum_{k=1}^{4} \hat{\Phi}^m(.) \left(\hat{\delta}_k^f - \hat{\delta}_k^m \right) \qquad (49)
\end{aligned}
$$

The left-hand side of the first line of equation (49) represents the difference in the average utility from jobs between similarly skilled female and male workers in occupation j and sector τ. The first line on the right-hand side represents the contribution to the utility gap 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 with the provision of a certain amenity in the job offer distribution. Specifically, it shows whether the predicted utility that women obtain from their employment relation would rise or fall relative to men if the female job offer distribution was characterized by the wage gains (or losses) associated with 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. Table 36 shows the results of the decomposition for workers at the median percentile of the CAT-ASVAB test in each career, defined by sector and occupation.

The first line of the table shows that women obtain higher utility from their jobs, on average, relative to men in administrative occupations and in executive occupations in the FIRE industry. This happens, however, simply because women are more likely than men to work in jobs offering benefits such as flexibility and parental leave and all workers value these benefits positively. Conditional on working for an employer who provides amenities, instead, women obtain strictly lower utility from their jobs than men in all careers. A comparison between lines (2a) and (2b) in table 36 shows that amenities do not appear to compensate women for the higher price they pay for their provision. Finally, due to gender differences in baseline wage offers, women also obtain lower utility than men in jobs that do not provide amenities in all careers.

Table 36: Predicted Utility Gap Decomposition - Female-to-Male

	(a) Administration, Education Health, Social Services			**(b) Financial Services**		
	Admin.	Executive	Professional	Admin.	Executive	Professional
Utility Gap	0.125	-0.579	-0.261	0.206	0.044	-0.026
			Utility Gap Components			
(1) Wage Offers	-0.239	-0.798	-0.466	-0.199	-0.384	-0.430
(2) Amenities Offers						
(2a) Through Wages	-0.124	-0.141	-0.142	-0.110	-0.125	-0.129
(2b) Through Preferences	-0.110	-0.096	-0.138	-0.140	-0.117	-0.163
(3) Selection	0.598	0.455	0.486	0.654	0.669	0.696

Notes: National Longitudinal Survey of Youth, 1997. Contribution of different factors to the gap in surplus from employment relationships between male and female workers. *Wage Offers* indicates the contribution of different wage offers by gender to the utility gap. *Amenities Offers Through Wages* shows the utility gap arising due to different wage offers to workers of different genders in amenity-providing jobs. *Amenities Offers Through Preferences* shows the contribution of gender-specific workers' preferences to the utility gap. *Selection* shows the utility gap arising due to gender-differences in the share of employees working for amenity-providing employers.