Essays in Labor Economics

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A dissertation

submitted to the Faculty of

the department of Economics

in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Boston College
Morrissey School of Arts and Sciences
Graduate School

June 2022

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Abstract

This dissertation consists of a collection of three essays in Labor Economics, all studying the careers of young American workers. The first two essays, Chapter 1 and Chapter 2, analyze the early-career gender wage gap among recent cohorts of highly educated US workers. The third essay, Chapter 3, analyzes long-run changes occurred over the last four decades in the supply of overtime work among American employees.

Chapter 1 provides an in-depth analysis of the evolution of the careers of *Millennial* American college graduates from labor market entry to five to ten years later. Using data from the National Longitudinal Survey of Youth (1997) I neatly reconstruct workers' careers from labor market entry and provide a variety of reduced-form evidence showing that gender differences in the wage gains that workers obtain when they change jobs determine a large portion of the early-career gender wage gap and of its expansion over years of experience. I show that these results are robust and hold irrespective of young workers' marital and parental status.

In light of the results provided in Chapter 1, in Chapter 2 I study the contribution of the main determinants of wage gains from job changes to the early-career gender wage gap among highly-educated American workers. Specifically, first, I

estimate a structural model of hedonic job search to estimate the extent to which men and women differ in terms of search frictions, of preferences for valuable amenities (flexibility and parental leave) and of the wage offers received conditional on the provision of amenities. Second, I use the model estimates to perform a series of counterfactual analyses and quantify the impact of search frictions, preferences and wage offers on the early-career gender wage gap and on its expansion due to job search and job changes. 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 that the model attributes to job search and job changes. 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%).

In Chapter 3 I study the determinants of long-run trends in overtime work. I document that work hours have been increasing in the United States in the 1980s and 1990s and steadily declining in the 2000s and 2010s, and that these trends were predominantly driven by secular changes in the share of young, salaried employees working long hours (more than 40 hours per week) in relatively high-pay jobs. I then provide a model that explains the evolving long-run trends in overtime as an outcome of underlying changes in labor demand that affected the life-cycle wage gains that employees expect to obtain when supplying overtime work hours. I empirically test and validate the implications of the model, and show that long-run changes in the wage premia for working long hours can explain the rise and fall in overtime work that I document. Finally, I estimate long-run trends in persistent and transitory wage dispersion and show that persistent wage dispersion grew in the 1980s and 1990s and declined later on. To the extent that shocks to wage gains from working long hours result into an increase in the spread of permanent income across employees typically supplying different amounts of work hours, I show that a rise and fall in wage premia for overtime work reconciles the observed reversed-U shaped trend in both overtime work and persistent wage dispersion. These results are suggestive that, after surging in the 1980s and the 1990s, the "fortunes of the youth" may have been declining later on, due to shifts in labor demand that flattened the life-cycle wage profiles that young, salaried employees can obtain when supplying long work hours. These results can also help reconcile recent evidence that the demand for skill and cognitive tasks and the college wage premium have been declining, while the age wage gap has been increasing. Conversely, the results I obtain question theories that explain long-run trends in US men's labor supply through secular increases in the marginal value of leisure due to improvements in leisure technology.

Acknowledgments

I wish to thank my advisors for their support and guidance as I worked on this dissertation. It was a privilege to know Claudia Olivetti, whose example keeps inspiring me and whose strength has broken so many barriers. Theodore Papageorgiou provided invaluable professional and personal support through the ups and downs of the last few years. Susanto Basu offered a number of brilliant remarks that improved my work and fostered my personal growth.

I also wish to thank Arthur Lewbel, who generously provided comments and feedback on my work, and Jaromir Nosal who, in few interactions throughout the years, taught me one or two things about Economics and about life.

I would have not been a Ph.D. student at Boston College without the selfless support of Francesca Bettio and Sauro Mocetti, to whom I am eternally grateful.

Navigating the conundrums of my Ph.D. was easier thanks to the skills and dedication of Gail Sullivan and Casey Eaton. Tracy Reagan greatly helped me as I juggled between my teaching duties and my research tasks.

Luca Gemmi has been an everlasting source of confidence, optimism, brotherhood and fun from the first first-year midterm exam to the latest presentation. Vittoria Dicandia, her strength and determination, boosted my motivation whenever I needed it the most. Valeria Ferraro held my hand in some of the most difficult moments I have experienced in the recent past. I deeply thank them all.

Throughout these years, my friends reminded me that my life and my person are much larger than a Doctoral degree. Their texts, an unexpected picture from our past, their book suggestions, some random emails, their feedback on my work, our phone calls and Zoom chats, their encouragement, our brief meetings or intense hugs gave me strength, happiness, and life. For all these things I am immensely grateful to them, and especially to Claudio Cordatore, Nicoletta Lupia, Francesca Montanari, Gian Lorenzo Spisso, Alice Elmi, Tiziana Salomone, Armanda Cetrulo, Marcello Gatti, Giulia Melotti, Consuelo Camerota, Paolo Santini and Riccardo Marchingiglio.

In spite of an Atlantic Ocean-distance, my father Enrico, my mother Margherita and my brother Carmine have been by my side on every step of this journey. For their trust and for their affection I thank them and all my surreal though very loving family.

Pierre De Leo is a unique human being and the most supportive, sensitive and feminist man I have ever known. I am privileged to share my life with him and to have been able to rely on him throughout these years. I cannot thank him enough.

I finally wish to thank Fabrizio Fiammanti and Sarah Piontkowski. They carried me on their shoulders, they brought me on my feet. If my life begins to resemble the one I have always imagined, that is because they helped me so much in figuring it out.

All errors are my own.

Ilaria D'Angelis

Contents

List of Tables

List of Figures

Chapter 1

Returns to Job Changes and the Early-Career Gender Wage Gap

1.1 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*a*, Light & Ureta 1995), they do not fully explain it.

In the first chapter of this dissertation I use reduced-form analyses to 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. Specifically, using data from the National Longitudinal Survey of Youth 1997 (NLSY97), I characterize the early-careers of *Millennial* college graduates and extensively document the characteristics of the dynamic increase in the gender wage gap over workers' early careers.

The results of my empirical analyses show that, even among recent cohorts of US workers, the average wage earned by workers does not differ by gender at labor market entry. Yet, 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. In addition, I show that the number of job changes workers' undergo during their early careers explains a large portion of the pay gap between young men and women. Importantly, while men and women change jobs similarly often, the wage changes associated with job changes tend to be lower for women, thus explaining approximately 75% of the pay gap. 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.[1]

Providing a comprehensive analysis of the evolution of the pay gap during the early careers of *millennial* American workers, I contribute to updating and expanding 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 US workers.

Throughout this dissertation, however, I move beyond the aforementioned literature. As I argue in this chapter, 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

[1] 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.

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. Reduced-form 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 chapter of this dissertation, 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.

This chapter is structured as follows. Section 1.2 describes the data and sample selection and illustrates the main characteristics of the workers I study. In section 1.3 I discuss the characteristics of the young men and women in my sample. In section 1.4 I illustrate the main results of my reduced-form analyses. In section 1.5 I provide a discussion of the results and concluding remarks.

1.2 *NLSY97* Data 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 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.[2]

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.[3] 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 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.

[2]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.

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

The final sample includes 311 male workers and 403 female workers, each observed for at least five years since labor market entry.[4]

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.

1.3 Descriptive Statistics

1.3.1 Characteristics of *Millennial* Men and Women

Tables 1.1 and 1.2 report the average characteristics of the male and female workers in the final sample and results of t-tests for differences in means. Table 1.1, 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 1.2 reports workers' hourly wage, hours and weeks worked in the first week in employment

[4]Appendix Section A.1 explains the construction of the final sample in more detail.

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 1.1 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% 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.

In line with existing literature, table 1.2 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 (Amano-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*a*, 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 A.9 and A.10 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 1.2, 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.

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 A.2 and A.7 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 1.1 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 1.2 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 A.4 and A.5 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 A.9 and A.10 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.[5]

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[5] 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.

1.3.2 Labor Market Transitions and Attachment by Gender

Tables 1.3 to 1.5 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 1.3 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 changes in the unique identifier of the employer where a worker is employed.[6]

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 1.4 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

[6]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.

they spend approximately 45 (men) and 57 (women) weeks out of labor later on.

Similar differences can also be observed in Table 1.5, 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 market entry, generating a non-negligible 8-weeks gap in labor force participation relative to men.

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.

1.4 Reduced-Form 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 reduced-form evidence that motivates the structural model I estimate in the second chapter of this dissertation and supports its results.

1.4.1 The Dynamic Expansion in the Gender Wage Gap

The two graphs in figure 1.1 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 A.3.1. In figure figure 1.1, 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 1.1 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 1.2. 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.

The wage patterns in figure 1.1 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 1.2 shows that the pay-gap does not arise as a consequence of the differential behavior of women who have children. Panel (a) in figure 1.2, 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.[7]

1.4.2 Gender Differences in Returns to Experience

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 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,

[7] Appendix figure A.1 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.

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.

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.[8] 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.

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

Where $J = 1, ..., 10$ is the year of 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

$$w_{it} = \alpha + \beta_0 \exp_{it} + \beta_1 \exp_{it}^2 + x_{it}' \delta + \varepsilon_{it} \tag{1.1}$$

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

$$w_{it} = \alpha + \sum_{\iota=1}^{I} \beta_\iota \exp_{i,\iota t} + x_{it}' \delta + \varepsilon_{it} \tag{1.2}$$

Where $\exp_{i,\iota t}$ = (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

[8] 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.

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.[9]

In Table 1.6, 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.[10]

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 1.6 (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, 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

[9] 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.

[10] Appendix Table A.11 reports the coefficient estimates from the different models. Appendix Table A.12 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.

when estimating the actual experience model.

1.4.3 Gender Differences in Returns to Job Changes

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 (1.1) 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.[11]

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), 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

[11] 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.

variable for female workers, I decompose the gender log-wage differential as

$$\hat{E}[w_{it}|f_i = 0] - \hat{E}[w_{it}|f_i = 1] = \sum_{k=1}^{K} \bar{x}_{kf}\left(\hat{\beta}_m - \hat{\beta}_f\right) + \sum_{k=1}^{K} \hat{\beta}_{mk}\left(\bar{x}_{km} - \bar{x}_{kf}\right) \quad (1.3)$$

The left hand side of equation (1.3) 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).[12] 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 1.3 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 1.3, 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 A.13 panel (a) shows the full set of results from the decomposition.

Panel (2) in figure 1.3 shows the results of the decomposition performed for

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

employees in executive and professional careers.[13] 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 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.

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.

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 the

[13] 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.

following regression

$$
\begin{aligned}
w_{it} = \alpha + \beta_1 \mathrm{exp}_{i,t-1} + \beta_2 \mathrm{exp}^2_{1,t-1} + \delta \mathrm{change\_job}_{i,t-1} + \\
+ \gamma \mathrm{change\_job}_{i,t-1} * \mathrm{exp}_{i,t-1} + \eta \mathrm{change\_job}_{i,t-1} * \mathrm{exp}^2_{i,t-1} + x'_{i,t-2}\psi + \varepsilon_{i,t}
\end{aligned}
\tag{1.4}
$$

Where $\mathrm{exp}_{i,t-1}$ 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 (1.4) 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 1.7 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 1.7 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%.

The evidence in Table 1.7 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

$$\begin{aligned} w_{it} = \alpha + \beta_1 \text{exp}_{i,t-1} + \beta_2 \text{exp}^2_{1,t-1} + \sum_{k=1}^{K} \delta_k \text{change\_job\_reason}_{k,i,t-1} + \\ + \sum_{k=1}^{K} \gamma_k \text{change\_job\_reason}_{k,i,t-1} * \text{exp}_{i,t-1} + \\ + \sum_{k=1}^{K} \eta_k \text{change\_job\_reason}_{k,i,t-1} * \text{exp}^2_{i,t-1} + x'_{i,t-2}\psi + \varepsilon_{i,t} \end{aligned} \tag{1.5}$$

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 1.8 shows the coefficients of interest from regression 1.4 (columns (1) and (2)) and from regression 1.5 (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 1.8 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.

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 1.5 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.[14] 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 1.5 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 1.9, 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

[14] In order to perform these quantifications, I use the average year of experience at first job change reported in table 1.1, and the average wage by year of experience reported in table 1.2 panels (a) and (b).

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%.

1.4.4 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

$$\begin{aligned} y^*_{ijt} &= z'_{ijt}\xi + \nu_i + u_{ijt} \\ &= \alpha + \beta w_{it} + \gamma \mathbf{I}\left[\text{Parental Benefits}_{ijt}\right] + \delta \mathbf{I}\left[\text{Flexible Schedule}_{ijt}\right] + x'_{ijt}\eta + \nu_i + u_{ijt} \end{aligned} \tag{1.6}$$

$$y_{ijt} = \mathbf{I}\left[j(t) \neq j(t+1)\right] = \mathbf{I}\left[y*_{ijt} \geq 0\right] \tag{1.7}$$

$$\Pr\left[y_{ijt} = 1 | z_{ijt}, \nu_i\right] = \frac{\exp\{z'_{ijt}\xi + \nu_i\}}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \tag{1.8}$$

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, $\mathbf{I}\left[\text{Parental Leave}_{ijt}\right]$ takes value 1 if employer j offers paid leave, unpaid leave or child care to i in t, $\mathbf{I}$ $\left[\text{Flexible Schedule}_{ijt}\right]$ takes value 1 if flexible schedule is available for i at employer j in year t. I am interested in observing whether the probability of job changes varies differently with wage and amenities between male and female workers. In order to account for other determinants of job change and potentially gender-specific search and mobility constraints, the models control for education, presence of children and marriage status. In addition, since mobility decreases with years since labor market entry, the model controls for a quadratic function of actual experience and years of tenure, and for the number of spells a worker spent out of the labor force. In order to account for labor demand factors, controls also include current occupation (9 categories) and industry (11 categories) dummies, union coverage, employer dimension and the US region-specific annual unemployment rate.[15]

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.[16]

Since within-individual changes over time in the outcome variable as well as in

[15] 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.

[16] A summary of Kitazawa (2012) theoretical argument is reported in Appendix Section A.7.

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 1.10, showing the Kitazawa (2012) elasticity (or semi-elasticity, depending on the definition of each regressor) of the rate of job quit.[17]

Table 1.10 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 1.10 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.

Interestingly, the estimated parameters in table 1.10 suggest that women and men may both have different preferences for amenities and face different job offer distributions. Regarding 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 1.10 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

[17] Appendix table A.16 reports the estimated vector of coefficients ξ, representing the partial effects of individual, employer and labor market specific characteristics on the log-odds ratio of job change.

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.

1.5 Conclusions

In this chapter I analyzed the early-career of highly educated *Millennial* American workers to study the contribution of job search and job changes to the gender wage gap and to its expansion over years of experience. The results of my analyses highlight 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 over time in the labor market, and more than half of the overall early-career wage gap is explained by gender specific wage gains and losses from job changes. Importantly, gains from job changes appear to be smaller for women irrespective of their marital and parental status. Hence, though events occurring after childbirth dramatically contribute to the expansion of the gender wage gap (Angelov, Johansson & Lindahl 2016, Cortes & Pan 2019, Bertrand, Goldin & Katz 2010*a*, Kleven, Landais & Søgaard 2019), young women appear to face smaller wage-growth prospects compared to their male counterparts even before (or irrespective of) childbirth. 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 reduced-form analyses. For these reasons, in the next chapter of this dissertation 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 to the gender pay gap and to its expansion over workers' early careers.

1.6 Tables

Table 1.1: 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 A.1 reports the time-invariant sample characteristics for 984 workers of all races and ethnicities. Appendix table A.3 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 A.4 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 A.5 reports the time-invariant sample characteristics for the subsample of 220 workers who do not marry by 2015.

Table 1.2: 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 A.2 and A.7 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 1.2. Appendix table A.6 reports the time-invariant sample characteristics for 984 highly educated workers of all races and ethnicities. Appendix table A.8 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 A.9 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 A.10 reports the time-invariant sample characteristics for the subsample of 220 workers who do not marry by 2015.

Table 1.3: 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 jobs	4.914	5.116	-0.202	0.609	1040
Gap in weeks between jobs | 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 jobs	6.604	8.148	-1.544	1.403	517
Gap in weeks between jobs | 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 1.1. 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 1.4: 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 1.1. 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.

Table 1.5: 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 1.1. 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 1.3. 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.

Table 1.6: Gains from Experience

	Males			Females		
	WH	AE	PE	WH	AE	PE
	(1)	(2)	(3)	(4)	(5)	(6)
	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: NLSY97. 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. WH = Work History model; AE = Aggregate Experience model; PE = 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.

Table 1.7: 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: NLSY97. 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.

Table 1.8: 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
Occ & Ind $t-2$	Y	Y	Y	Y

Notes: NLSY97. Sample as in Table 1.1. 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 A.14 reports the full-set of models (1) and (2) estimated coefficients in different specifications. Appendix table A.15 reports the full-set of models (3) and (4) estimated coefficients in different specifications.

Table 1.9: 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
Occ & Ind $t-2$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: NLSY97. Sample as in Table 1.1. All models include the same control variables as in table 1.8 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. (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 differ between unmarried workers and workers who are married or anticipate a forthcoming marriage occurring by t. Following a similar logic, (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, 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. These models interact experience, the job change dummy and their interaction with indicators taking value 1 for workers who, respectively, marry or have a child by 2015.

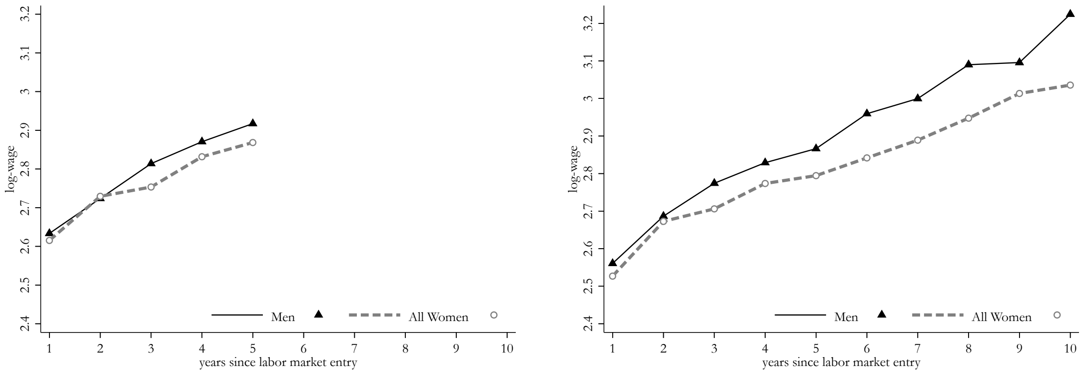
Table 1.10: Conditional Logit Models of Job Quit

	Males	Females
I[Job($t+1$) $\neq$ Job]		
Log-Hourly Wage in 2005 USD	-0.3818***	-0.6458***
	(0.1343)	(0.1563)
I[Parental Benefits Available at j]	-0.2746***	-0.2672***
	(0.1016)	(0.1027)
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: NLSY97. Sample as in Table 1.1. 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.

1.7 Figures

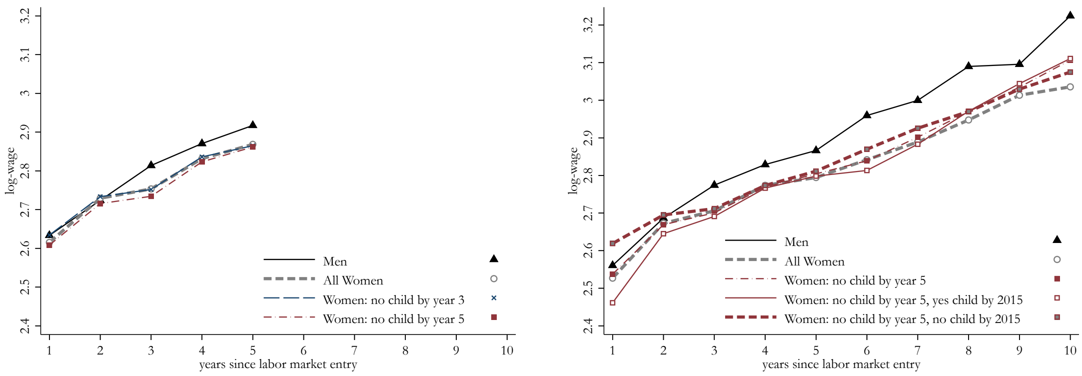
Figure 1.1: Composition Adjusted Mean Log-Wages - All Workers



(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 A.3.1.

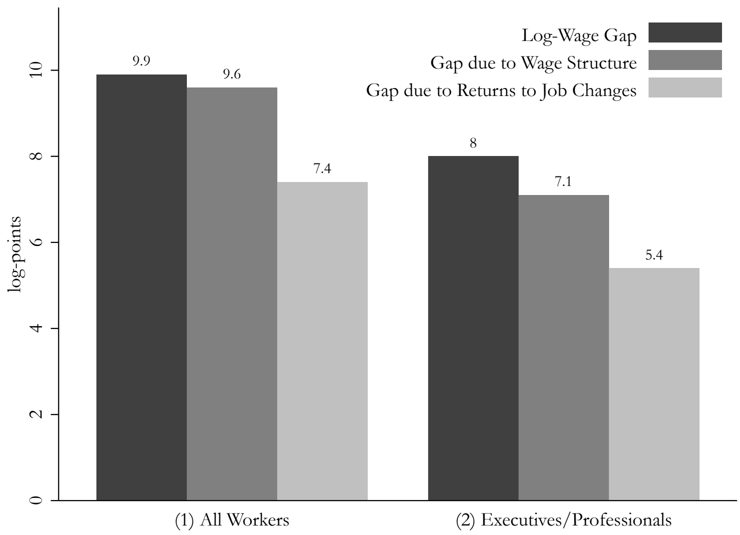
Figure 1.2: Composition Adjusted Mean Log-Wages - Women By Parental Status



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

Notes: National Longitudinal Survey of Youth, 1997. Samples as in figure 1.1. Appendix figure A.1 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.

Figure 1.3: Wage Gap Decomposition - Selected Workers Categories



Notes: National Longitudinal Survey of Youth, 1997. Sample as in Figure 1.1 Panel (a). 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 A.13 shows the complete set of results of the wage gap decomposition. Appendix figure A.2 shows that the results 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.

Chapter 2

The Search for Amenities and Early-Career Gender Wage Gap

2.1 Introduction

In Chapter 1 I showed that gender-specific wage gains from job changes explain a non-negligible portion of the early-career gender wage gap among *Millennial* highly-educated workers. Building on this evidence, in this Chapter 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 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

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[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.

[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

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.

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

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.

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,[4] 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.[5]

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[4]See, for example, Claire Cain Miller, "Lowe's Joins Other Big Employers in Offering Paid Parental Leave", *The New York Times* February 1 2018; Claire Cain Miller, "Walmart and Now Starbucks: Why More Big Companies Are Offering Paid Family Leave", *New York Times* January 24, 2018; Sarah Halzack "Workplace Flexibility Can Be Key to Recruiting and Retaining Top Workers", *The Washington Post* December 2 2012; Olga Khazan, "Give Up on Work-Life Balance", *The Atlantic* May 30 2019; Jennifer Ludden, "When Employers Make Room for Work-Life Balance", *NPR* March 15 2010; Joan Michelson, "How Small Companies Can Offer Great Paid-Leave Programs", *The Harvard Business Review* January 7 2021; Sue Shellenbarger "Fairer Flextime: Employers Try New Policies for Alternative Schedules", *The Wall Street Journal* November 17 2005;

[5]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

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

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).

from employment relationships 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 chapter is structured as follows. In section 2.2, I explain the contribution of this paper to the related literature. Section 2.3 describes and discusses the hedonic search model I estimate, and explain its estimation and the identification of the parameters of interest. In section 2.4 I illustrate and interpret the model estimates and use counterfactual analyses to quantify the impact of preferences, search frictions and job offers on the early-career gender wage gap and on its expansion over years of experience. Section 2.5 concludes.

2.2 Related Literature

In this Chapter I build 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, to contribute to the fast growing literature that accounts for the role of certain valuable amenities in determining the gender pay gap throughout workers careers.

Three recent works by Liu (2016), Amano-Patiño, Baron & Xiao (2020) and citet*LeBarbanchon2021 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.[6]

This paper and its findings are also related to a recent contribution by Amano-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

[6] 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).

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 Amano-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 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.

Finally, the work by Le Barbanchon, Rathelot & Roulet (2021) relies on administrative data to show that gender-differences in preferences for commuting determine approximately 14% of the residual gender wage gap in France. The authors then use job-application data to provide further evidence that their findings are not driven by unobserved differences in the sets of jobs offered to men and women. These findings are relevant as they suggest that part of the gender-differences in wage offers that I estimate in this paper may be driven by underlying unobserved differences in preferences for commuting between American male and female workers. Such differences in preferences (if any) should reflect into different wage offers unconditional on the provision of flexibility and parental leave, thus further highlighting the need to account for potential heterogeneity in the wage offer distribution that men and women face before estimating the price of flexibility and parental leave and workers' preferences for these benefits.

2.3 Modeling the Search for Amenities

2.3.1 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).[7]

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

$$u^g(w, \mathbf{a}) = w + \delta^{g\prime}\mathbf{a} \tag{2.1}$$

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

[7]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.

amenity a_k.

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

$$P^g(\text{leave}|w, \mathbf{a}) = q^g + \lambda_2^g + \lambda_1^g \bar{F}_u^g(w + \delta^{g\prime}\mathbf{a}) \tag{2.2}$$

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 ($\lambda_1^g \bar{F}_u^g(w + \delta^{g\prime}\mathbf{a})$).

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

$$\lambda_0^g U^g = q^g(1 - U^g) \tag{2.3}$$

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

$$\begin{aligned}\lambda_0 U F_u(u|.) + \lambda_2 F_u(u|.)(1-U)\bar{G}_u(u|.) = q(1-U)G_u(u|.) + \lambda_2 \bar{F}_u(u|.)(1-U)G_u(u|.) + \\ + \lambda_1 \bar{F}_u(u|.)(1-U)G_u(u|.)\end{aligned} \tag{2.4}$$

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

$$G_u(u|.) = \frac{F_u(w + \delta'\mathbf{a}|.)}{1 + k\bar{F}(w + \delta'\mathbf{a}|.)} \tag{2.5}$$

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

$$\frac{g(w, \mathbf{a}|.)}{g_u(w + \delta'\mathbf{a}|.)} = \frac{f(w, \mathbf{a}|.)}{f_u(w + \delta'\mathbf{a}|.)} \tag{2.6}$$

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

$$g(w, \mathbf{a}|.) = (1 + k)\frac{f(w, \mathbf{a}|.)}{[1 + k\bar{F}(w + \delta'\mathbf{a}|.)]^2} \tag{2.7}$$

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 2.7 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.

2.3.2 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.[8]

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

[8] 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 1.3.2. For this reason, the model I estimate does not allow for different search behaviors between the unemployed and workers out of the labor force.

remaining occupations. The four industry classes are: *education, administrative, health* (omitted); *finance*, *trade* and *other*.

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

The 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.

$$w^*(b, \mathrm{car}_{occ}, \mathrm{car}_{ind}) = \mu_0^w + \mu_1^w b + \rho' \mathbf{a}^* + \sum_{occ=1}^{3} \varphi_{occ}^w \mathrm{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^w \mathrm{car}_{ind} + \sigma_w \varepsilon_w \tag{2.8}$$

$$a_k^*(b, \mathrm{car}_{occ}, \mathrm{car}_{ind}) = \mathbf{1}\{\mu_0^{a_k} + \mu_1^{a_k} b + \sum_{occ=1}^{3} \varphi_{occ}^{a_k} \mathrm{car}_{occ} + \sum_{ind=1}^{3} \varphi_{ind}^{a_k} \mathrm{car}_{ind} + \varepsilon_{a_k} > 0\} \tag{2.9}$$

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 $w^*(b, \mathrm{car}_{occ}, \mathrm{car}_{ind})$ 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

$$l_{t_0} = \left(\frac{q}{\lambda_0 + q}\right)^{1-e_{t_0}} \left(\frac{\lambda_0}{\lambda_0 + q}\right)^{e_{t_0}} g_{t_0}(w_{t_0}, \mathbf{a}_{t_0}|.)^{e_{t_0}} \tag{2.10}$$

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

$$\begin{aligned} l_{t+1} = & \, q^{ju_t}[1-\lambda_0]^{uu_t} \times \\ & \times \lambda_0^{uj_t} f_{t+1}(w_{t+1}, \mathbf{a}_{t+1}|.)^{uj_t} \times \\ & \times [1 - \lambda_1 \bar{F}(u_t|.) - \lambda_2 - q]^{s_t} \times \\ & \times [\lambda_1 \mathbf{1}\{w_{t+1} + \delta' \mathbf{a}_{t+1} > w_t + \delta' \mathbf{a}_t\} + \lambda_2]^{jj_t} f_{t+1}(w_{t+1}, \mathbf{a}_{t+1}|.)^{jj_t} \end{aligned} \tag{2.11}$$

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

$$l(.) = l_{t_0} \prod_{t=t_0}^{T} l_{t+1}(e_{t+1}, w_{t+1}, \mathbf{a}_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, w_t, \mathbf{a}_t, b, \text{car}_{occ}, \text{car}_{ind}) \tag{2.12}$$

The likelihood function is

$$L(.) = \prod_{i=1}^{N} l_{t_0,i} \prod_{t=t_0}^{T} l_{t+1,1}(e_{t+1}, w_{t+1}, \mathbf{a}_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, w_t, \mathbf{a}_t, b, \text{car}_{occ}, \text{car}_{ind}) \tag{2.13}$$

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 (2.11) and, consequently, in equation (2.13), because of the assumptions of normality and independence of the unobservables in the job offers.[9]

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.[10] I estimate the model separately for men and women.

[9] Appendix Section B.1 shows how to derive the functional forms for $f(w^*, \mathbf{a}^*|.)$ and $\bar{F}_u(u|.)$.

[10] Appendix Section B.2 describes the estimation procedure in greater detail.

2.3.3 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.

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 2.1 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 2.1 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 2.1 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.

2.4 Results

2.4.1 Parameter Estimates

Tables 2.1, 2.2 and 2.3 report the structural parameter estimates.[11] Regarding search frictions, Table 2.1 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.[12]

The result is particularly interesting in light of the descriptive evidence collected in section 1.3.1. 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 2.2 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.[13]

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[11] Table 2.1 reports the asymptotic standard errors in parentheses, and tables 2.2 and 2.3 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.

[12] 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.

[13] The magnitude of the estimated preferences coefficients is consistent with the magnitude of the preferences for amenities such as job security, that Bonhomme & Jolivet (2009) estimate on a sample of European men.

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.[14]

Table 2.3 reports the estimated features of the distributions of wages offered to male and female workers.[15] 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.

Regarding schedule flexibility, jobs offering such benefit entail 11 log-points

[14] As table B.1 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.

[15] The structural parameter estimates regarding the offer of amenities are reported in the Appendix Section B.3.

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.[16]

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.[17] 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 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

[16] 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.'

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

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 1.7, 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.

2.4.2 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 2.4, panel (a) line (1)). The second counterfactual exercise predicts women's wages if workers' utility was not affected by benefits and job attributes (table 2.4, panel (a) line (2)).[18]. In the remaining counterfactual exercises, I predict the wages women would obtain if search environments, preferences, and job offers were the

[18]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.

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 2.4.

The first rows in panel (a) and panel (b) of table 2.4 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.[19] 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

[19] 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.

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 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 2.4 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 1.1.

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

Figure 2.2 plots the growth path of the early-career wages predicted by the model.[20] 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 2.2, 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

[20]The career-specific predicted and counterfactual wage growth paths for female workers are reported in figures B.1, B.2, B.3 and B.4 in the Appendix.

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 1.1. 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 2.2, 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 (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.[21]

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

[21] 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.

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-providing jobs equaled the mean wage offered to men. The red, dotted line in figure 2.2 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 B.5.

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.

2.5 Conclusions

In this chapter I estimated a model of hedonic job search to quantify the extent to which search frictions, preferences for non-wage attributes such as flexibility and parental leave, and jobs offers, explain the early career gender wage gap among *Millennial* college graduate American workers. 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 reflecting gender heterogeneity in preferences over these work-life-balance enhancing benefits. 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 other factors including gender-based differences in occupational choices (Goldin 2014, Blau & Kahn 2017), differences across genders in returns to tenure (Barth, Olivetti & Kerr 2021), the likelihood of obtaining promotions (Booth, Francesconi & Frank 2003, Gicheva 2013) and the asymmetric impact of childbirth on men and women (Angelov, Johansson & Lindahl 2016, Kleven, Landais & Søgaard 2019) also affect the gap. 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 to be attributed to job search and job changes, 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 highlighted in this chapter 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.[22]

[22] 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.

2.6 Tables

Table 2.1: 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.

Table 2.2: 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 B.1 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. $e^{-\delta_k} = \frac{w(a_k=1,u)}{w,(a_k=0,u)}$

Table 2.3: 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)

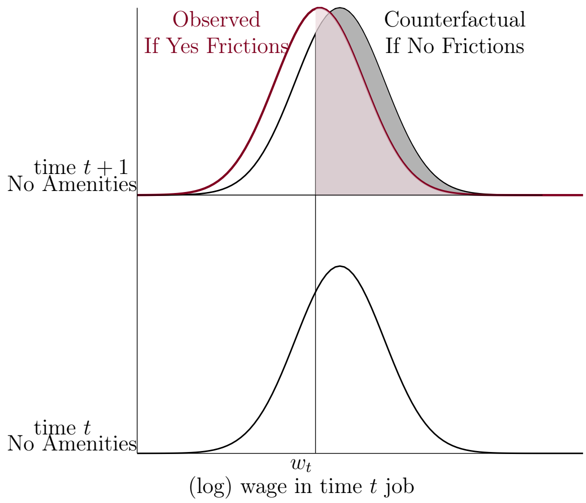
Table 2.4: Predicted Gender Wage Gap

	(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

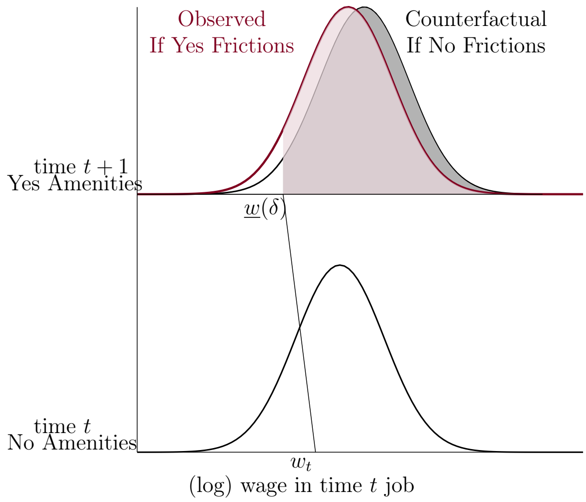
Notes: National Longitudinal Survey of Youth, 1997. Actual and counterfactual wages by workers' careers in different scenarios. Counterfactuals are computed assuming that women are homogeneous in ability within careers. The industry and occupation median value of the CAT-ASVAB test percentile is used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

2.7 Figures

Figure 2.1: The Identification of λ_1 - An Illustration



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

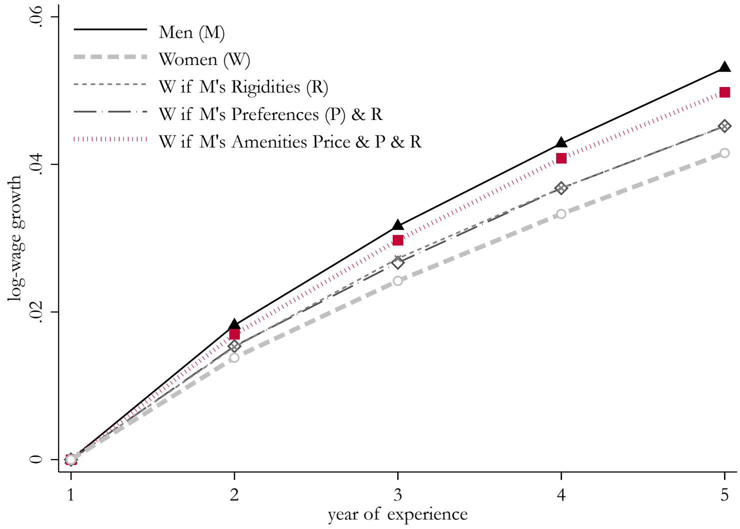


(b) Job-to-Job Transitions: No Amenities in t, Yes Amenities in $t+1$

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.

*

Figure 2.2: 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.

Chapter 3

The *Underworked* American? Explaining Long-Run Trends in Overtime Work

3.1 Introduction

The debate around work-life balance and overtime work is heated in the United States. A number of scholars studied *overwork* (Schor 1991, McCallum 2020), highlighted its possible consequences on workers' well-being (Boushey & Ansel 2017), and analyzed its impact on earnings inequality both within and across demographic groups (Costa 2000, Cortes & Pan 2019, Gicheva 2013, Goldin 2014). The intense public interest surrounding long work-hours is not surprising, given that American workers tend to work considerably more than workers in other advanced economies.[1]

It is well-known that work-hours and overtime work have been falling in the United States since the 1890s (Vanderbroucke 2009) and that the declining trend in the length of the workday continued until the 1970s (Costa 2000). Since the

[1]OECD (2021), Hours worked (indicator). doi: 10.1787/47be1c78-en (Accessed on 04 February 2021)

1970s, however, work hours have been increasing (Kuhn & Lozano 2008, Michelacci & Pijoan-Mas 2011). In particular, the upper tail of the weekly hours distribution rose between the 1970s and the 1990s, driven by an increase in work-hours among college educated workers (Coleman & Pencavel 1993). Consequently, the share of employees working more than 48 hours per week also steadily increased during the same time interval (Rones, Randy & Gardner 1997). Highly paid salaried employees predominantly determined the observed surge in the length of the workday (Kuhn & Lozano 2008).

While long work-hours still characterize the United States relative to other countries (Blundell, Bozio & Laroque 2011), in this chapter I document that, following their well-known increase in the 1980s and 1990s, weekly work hours and the share of employees working long hours steadily declined in the U.S. in the 2000s and 2010s. The trend reversal in the incidence of long workweeks is quantitatively strong. As a matter of fact, I show that the share of salaried employees working more than 48 hours per week was as high in 2018 as it was at the beginning of the 1980s. Specifically, around 32% of salaried employees worked more than 48 hours per week in 1982 and in 2018. The share had peaked at 42% in the mid of the 1990s. I then show that the rise and fall in work hours can be explained by secular changes in labor demand that affected the pay premia that employees working long hours can expect to earn throughout their life-cycle.

This work provides several contributions to the literature. First, this work is among the first to provide evidence that the weekly hours worked by American employees have been steadily declining in the 2000s and 2010s, reversing the rising trend that the previous literature has documented (Kuhn & Lozano 2008, Michelacci & Pijoan-Mas 2011). This work thus introduces a relatively new stylized fact, and adds to the literature studying trends in the labor supply of American workers, that so far focused most prominently on studying the secular rise in women's labor force participation (Bailey 2004, Blau & Kahn 2013, 2017, Goldin 2006, Fernández, Fogli & Olivetti 2004, Olivetti 2006, Olivetti & Petrongolo 2016) and the more recent decline in men's labor force participation and employment (Aaronson, Fallick, Figura & Wascher 2006, Abraham & Kearney 2018, Juhn & Potter 2006, Krueger 2017).

To the best of my knowledge, Aguiar, Bils, Charles & Hurst (2017) are the first who noticed that work hours declined among male American employees in the 2000s and 2010s, and explain this phenomenon through improved leisure technology that mostly contributed to a decline in the labor supply of young men and to an increase in non-participation among these workers. The second contribution of this work is to provide an in-depth empirical analysis of the characteristics of both the 1980s-1990s rise and 2000s-2010s fall in work hours and in the share of employees working long hours. This allows me to isolate a number of stylized-facts that any theoretical explanation for the phenomenon should be able to explain, and that are not necessarily consistent with the theory proposed by Aguiar, Bils, Charles & Hurst (2017).

Specifically, using data from the CPS Merged Outgoing Rotation Groups (ORG) and from the Panel Study of Income Dynamics (PSID), I show that the 1980s-1990s rise and the mid-1990s-2010s fall in weekly work hours among full-time workers were driven by relatively young salaried employees mostly employed in high-pay professional occupations. Among employees paid by the hour, instead, weekly hours remained fairly constant over the last four decades. I further show that the rise and fall in work hours cannot be explained secular transformations of the US labor market, including changes in the gender and age composition of the workforce and changes in the distribution of employment across occupations leading to employment polarization (Autor, Katz & Kearney 2006, 2008): work hours rose and fell over the last forty years within workers of the same gender, within age groups, and within occupations. Finally, I show that the secular rise and fall in weekly work hours among US workers was entirely determined by the contemporaneous growth and decline in the share of salaried employees working more than 40 hours per week: conditional on typically working overtime (more than 40 hours per week), straight-time (between 30 and 40 hours per week), or part-time (between 5 and 30 hour per week) weekly hours remained roughly constant over the last four decades among salaried employees and among all US employed workers alike. This evidence directly questions the Aguiar, Bils, Charles & Hurst (2017) hypothesis that improvements in leisure technology (e.g. videogames) contributed to an increase in workers' reservation wage and prompted workers to substitute leisure for work hours at the intensive margins.

The third contribution of this work is to provide a unified explanation that can reconcile all the above-mentioned stylized facts. In particular, I use the model that Gicheva (2013) built to explain the convex relation between pay and work hours, and show that it can predict long-run changes in overtime work that are fully consistent with the rise and fall in the share of employees working long hours that I document. The model explains employees' decision to work long-hours based on the wage gains that workers expect to obtain over their life-cycle when promoted to high-level jobs. Specifically, two-periods living workers are heterogeneous in their skills and in their taste for leisure, and maximize their life-cycle utility by choosing their optimal supply of work hours in every period of their life. Conditional on their optimal choice of work hours, employees decide which type of career they wish to pursue. There exist two types of careers that workers can pursue: one career has workers performing the same tasks (i.e. remaining in the same job position) in both periods of their life; the other career involves a promotion to a higher-level job in the second period of workers' life. In the high-level job output is more sensitive to workers' skills than in the low-level job, and workers acquire skills the more hours they work during their first period of life.

In this framework, with workers and employers having full information on the set-up of the economy and on workers' types, employees optimally self-select into different careers depending on their distaste for work hours, and employees who select into careers involving promotions work longer hours. In addition, changes in the pay gains from promotions changes workers' optimal choices consistently with what I observe in the data.

First, when the wage per unit of labor that workers in high-level jobs obtain increases, more employees self-select into careers involving promotion paths, hence the share of employees working long-hours increases. The reverse occurs when the life-cycle premia from working long hours decline. Second, when the life-cycle premia from working long hours increase, conditional on their ability and distaste for work hours, all employees on promotion career paths work longer hours, thus contributing to an increase in the average hours in jobs that typically require long workweeks. Yet, as more workers with high distaste for work hours self-select into promotion career-paths, they contribute to a decline in average hours within long-hours jobs. These two effects tend to counteract each other, potentially leaving the average hours worked in long-hours jobs unaffected in spite of changes in the wage premia associated with working long hours. Third, as workers with stronger ability to learn-by-doing increase their productivity faster when working long hours and ability to learn may decrease in age, young workers are predicted to be more sensitive to changes in the wage incentives to work long hours. These implications of the Gicheva (2013) model are fully consistent with the stylized facts I document.[2]

To further corroborate the hypothesis that a secular rise and fall in the life-cycle premia from working long hours drove the observed trends in work hours and overtime work, I use the model Gicheva (2013) to derive empirical relations between wage growth and past work hours that I directly test and validate using PSID data.

The fourth contribution of this paper is to refine and clarify the inequality-hours hypothesis (Bell & Freeman 2001). According to the inequality-hours hypothesis, the dispersion in the wage distribution proxies the life-cycle wage gains that work-

[2]Crucially, the model is especially well-suited to explain the decision to work long-hours among US salaried employees, the latter being exempt from receiving immediate overtime wage premia when supplying more than 40 hours per week under the Fair Labor Standards Act of 1938 (Whittaker 2003, 2005, Hamermesh 2002).

ers can expect to obtain when working longer hours. For this reason, work hours and overtime work should be positively correlated with wage dispersion. While the hypothesis, initially formulated by Bell & Freeman (2001), has been used by Kuhn & Lozano (2008) and Michelacci & Pijoan-Mas (2011) to explain the surge in work hours and overtime work observed in the US in the 1980s and 1990s, here I show that there is no robust positive relationship between overall wage dispersion and work hours. I also provide evidence that long-run trends in overall wage dispersion are inconsistent with long-run trends in overtime work, and show that most of the secular growth in wage dispersion occurred in the US between the 1980s and the 2010s was driven by factors that are not suitable to proxy long-run changes in the life-cycle wage premia for working overtime.

In particular, I use the Gicheva (2013) model to argue that changes in the life-cycle premia from working overtime should result into changes in the dispersion of permanent income across individuals, but not into changes in the dispersion of transitory income shocks. If long-run trends in overall wage variance mostly capture underlying trends in the variance of transitory income shocks, then, the former are not suitable to test the inequality-hours hypothesis in the data. I hence implement the methodology proposed by Heathcote, Storesletten & Violante (2010) to separately identify the time-varying variance of permanent and transitory income shocks and, using PSID data, I show that the dispersion of transitory wage shocks has been surging between the 1980s and the 2010s, while the variance of permanent wage shocks has been rising between the 1980s and the mid-1990s and declining later on.

This evidence confirms and extends the results earlier obtained by Gottschalk & Moffitt (1994, 1999, 2009), Heathcote, Storesletten & Violante (2010), providing further evidence that a surge in income volatility has been a leading cause of the long-run trends in overall wage inequality. Most importantly, the results I obtain confirm that permanent wage dispersion has been rising in the time period where overtime work increased and falling in the decades when the decline in overtime work was observed. This fact is fully consistent with the idea that the life-cycle premia from working overtime have been rising between the 1980s and the 1990s and declining later on, driving the growth and decline in persistent wage dispersion and in overtime work.

While other models exist that imply a positive relationship between wage dispersion and work hours, I finally discuss why the Gicheva (2013) mechanism relying on learning-by-doing and human capital accumulation is more effective than theories based on signaling (Anger 2008), screening (Landers, Rebitzer & Lowell 1996) and incentive schemes (Lazear & Rosen 1981) to explain the stylized facts that I document.

The results I provide in this work are suggestive that the rise and fall in overtime work that I document are driven by underlying structural changes to labor demand that contributed to a reversed-U shaped trend in the wage premia for overtime work. As these changes mostly affected young, salaried workers in relatively high-pay jobs, my results also suggest that the "fortunes of the youth" (Beaudry, Green & Sand 2014) may have been rising and falling over the last four decades. As a matter of fact, my results are broadly consistent with findings that the demand for skills and cognitive tasks may have been declining in the 21st century (Beaudry, Green & Sand 2016), they can help explain the recently observed decline in the college wage premium (Valletta 2016, Autor, Goldin & Katz 2020) in the United States, and are in line with emerging evidence that the age wage gap has been rising from the 1990s in advanced economies including the US (Bianchi & Paradisi 2021). These findings, in turns, question the hypothesis that the 2000s-2010s fall in work hours was mostly determined by a secular increase in the marginal value of leisure (Aguiar, Bils, Charles & Hurst 2017).

This chapter is structured as follows. In section 3.2 I show and discuss the main stylized facts that I aim at explaining, namely, the 1980s-1990s rise and the 2000s-2010s fall in work hours and in the share of employees working overtime. Section 3.3 summarizes the Gicheva (2013) model, discusses its main implications and tests them. In section 3.4 I discuss the inequality-hours hypothesis, show its apparent inconsistency with the stylized facts I document, refine it, provide evidence of its validity and analyze it through the lens of the Gicheva (2013). Section 3.5 concludes.

3.2 Stylized Facts: Long-Run Trends in Overtime Work

3.2.1 Data

I study trends in long hours using data on full time male employees from the Current Population Survey Merged Outgoing Rotation Groups (ORG) and from the Panel Study of Income Dynamics (PSID), in the time span that goes from 1979 to 2018. In this project, the terms overtime work, long hours or long workweek are all used to indicate work-weeks longer than 40 hours or longer than 48 hours, depending on the analysis performed. Workers are defined to work overtime (or long hours) if they usually work more than 40 (48) weekly hours at their main job.

Throughout the analysis, I focus on 25 to 64 year-old full-time male workers who are not self employed. I exclude employees working less than 30 or more than 98 hours per week. I also exclude workers with missing observations on wages or earnings, and workers whose hourly pay is outside the interval between 1 to 100 real dollars. Wages are expressed in 1985 $ terms, and deflated using the All Consumers CPI from the Bureau of Labor Statistics. In CPS-ORG data I multiply top-coded earnings by a factor of 1.4 (Lemieux 2006). For ORG data I construct hourly wages using information on usual weekly earnings and usual weekly work-hours. I define workers to be salaried if they report not to be paid on a hourly basis. For PSID data I construct hourly wages using information on annual earnings, annual weeks worked and usual weekly hours at employees' main jobs. I define workers to be salaried if they report to be paid on a salary basis at their main job. To increase compatibility with ORG data, I also perform certain analyses on the sample of all PSID workers who are not paid by the hour.

3.2.2 The Rise and Fall in Overtime Work

Figure 3.1 panel (a) shows the main fact of interest in this paper. The figure plots the share of CPS-ORG employees usually working more than 40 hours per week and the average weekly work hours, between 1979 and 2018. The statistics are computed separately for all workers, for workers paid by the hour and for workers who are not paid by the hour. From now on, I will refer to the latter category of workers as salaried workers.

As previously observed in the literature, the share of employees working long hours (or long workweeks) rose between the 1980s and the 1990s. 25% of full-time employees worked more than 40 hours per week around 1982, and 30% of them worked long hours in the 1990s. It was also observed in the literature that the increasing incidence of long hours mostly involved salaried employees Kuhn & Lozano (2008). While 35% of salaried employees worked more than 40 hours per week at the beginning of the 1980s, around 45% of salaried employees worked long hours in the 1990s.

The incidence of long workweeks, however, began to decrease since the late 1990s, especially among salaried workers. By 2018, the share of long hours salaried employees was almost identical to its level at the beginning of the 1980s: it steadily decreased by more than 10 percentage points between the mid 1990s and 2018. In Appendix section C.1 I report the results of testing for a break in the time series of the share of long-hours employees and in the time series of average usual weekly work-hours (table C.1). They suggest that the reversal in its rising pattern occurred around 1995.

In panel (b) of figure 3.1, salaried workers are split between college graduates ("Coll", thick black line) and workers without a college degree ("No Coll", thin black line). The rise and fall in the share of salaried employees working long hours are evident and quantitatively large for both categories. In addition, for both college graduates and workers without a college degree the likelihood of working long work-weeks mostly increased during the 1980s and flattened in the 1990s before steadily dropping from then on.

3.2.3 Alternative Definition of Overtime and Alternative Data

In figure 3.2 I show that both the rise and fall in the share of long hours salaried employees are consistent with alternative definitions of long workweeks and are evident across different datasets. This check is relevant, since questions regarding work hours changed during a major revision to the CPS survey occurred in 1993. Rones et al. (1997) show that the number of employees working exactly 40 hours per week fell considerably between 1993 and 1994, while the share of employees working between 41 and 48 hours rose, possibly as a consequence of the revision.[3]

In order to address concerns regarding the impact of the CPS survey revision on trends in long hours, in panel (a) I plot the share of employees usually working more than 40 hours per week and the share of employees working more than 48 hours per week. In panel (b) I plot the same quantities for salaried workers split by education groups. As the figures show, both the rise and fall in the share of long-hours employees remain largely unaffected for salaried workers when the definition of long-hours changes. It implies that the reversed U-shaped long-run trend in overtime work is not an artifact of changes occurred in the CPS questionnaire.

Additional data sources provide further evidence supporting the robustness of the rise and fall in the incidence of long workweeks in the United States. Figure

[3]Reducing errors in measuring work hours was among the main rationales beyond the 1993-94 revision to the CPS questionnaire. For this reason, the order of the survey questions asking about the number of hours worked during the previous week changed. The questions themselves slightly changed in order to elicit workers' precision in reporting the number of hours they spent working during the previous week. In this project, I do not use the variables capturing the number of hours worked in previous week, but the variables capturing the number of hours "usually" worked.

3.7 panel (a) shows trends in the shares of full-time employees working long hours in the Panel Study of Income Dynamics (PSID). In the figure, black symbols refer to workers with a college degree, while gray symbols refer to workers with any level of education. The solid lines show the trends in the share of long-hours employees among all workers who are not paid on a hourly basis. These workers closely correspond to the definition of CPS salaried workers.[4] The triangle-marked lines isolate PSID workers who are paid on a salary basis.

Panel (a) shows that the share of long-hours employees markedly increased in the 1980s and during part of the 1990s, but it fell thereafter among 25 to 64 year-old workers. Panel (b) restricts the samples to 25 to 44 year-old workers, and shows that the decreasing pattern in the incidence of long hours observed in the last two decades is almost symmetric to the previous two-decade increase.

3.2.4 Long Work-Weeks by Age Groups

Panel (b) in figure 3.7 captures an important feature of the rise and fall in the incidence of long workweeks. Namely, the rise and, mostly, fall in the share of long-hours employees primarily involved relatively young workers. The age dimension in the rise and fall in overtime work is also evident in CPS data. Figure 3.4 shows that, while the incidence of long workweeks increased in the 1980s and 1990s for workers of all ages, it primarily fell among workers below 44 years of age thereafter. This fact is evident for both college graduate workers (black solid line) and for workers without a college degree (gray dashed line). As panels (a) and (b) show, in 2018 the share of 25-44 year-old salaried employees working long hours had returned at its 1980 level.

In table 3.1 I show that the rise and fall in the share of young overtime salaried

[4]The CPS Outgoing Rotation Groups allow to distinguish workers paid on a hourly basis from workers who are not paid on a hourly basis. However, it is not possible to disentangle whether CPS employees who are not paid by the hour are paid on a salary basis, by commission, by piece-rate or by any alternative payment method. In the PSID sample, 79% of workers who are not paid by the hour are salaried. The share of salaried workers is 89% among college graduates who are not paid by the hour, and 69% among workers without a college degree who are not paid by the hour.

employees in fact drove the overall reversal in the long-run trends in overtime work. Line (1) of table 3.1 shows that the age composition of the US workforce has been changing over the last four decades, as the share of 25-44 year-old workers over all employees steadily declined from 65.6% in the Eighties to 53.3% between 2013 and 2017. Even though the age composition of the salaried workforce changed dramatically between the 1980s and the 2010s, this phenomenon did not mechanically determine the observed changes in the incidence of long-hours. If the share of young workers among full-time salaried employees had remained at its 1983-87 level, the time pattern in the share of long hours employees (line (5)) would have been similar to its observed pattern (line (4)).

Line (6) in table 3.1, instead, shows that the time pattern in the incidence of long work-weeks would have been considerably flatter across decades if the share of long-hours employees had not changed over time among relatively young salaried workers. Keeping the share of young long-hours salaried employees constant at its 1983-87 level, the likelihood of working long work-weeks across all age groups would have increased by less than 3 percentage points between the Eighties and the Nineties. Given the observed time trend in overtime work (line (4)), the counterfactual exercise reported in line (6) suggests that the rising share of 25-44 year-old employees working long work-weeks explains 61% of the overall incidence in long work-weeks among American salaried employees observed between the 1980s and the mid-1990s. The role of young workers in determining long-run trends in overtime work is even more pronounced when analyzing the declining incidence of long work-weeeks between the 1990s and the 2010s. Had the share of employees working long-hours among young workers remained constant at its 1983 level, the overall share of long-hours employees would have fallen by 0.7 percentage-points between 1993-97 and 2013-17. It implies that the decline in the likelihood of working long-hours among young workers explains 89% of the 6.5 percentage-points decline in the share of long-hours employees observed between the 1990s and the 2010s.

Analyzing the life-cycle profiles of workers' labor supply by cohorts further highlights the role played by young workers in determining long-run trends in overtime work. In figure 3.5 I plot the share of salaried employees working overtime across five-year intervals between 1980 and 2015. Workers are split in cohorts defined by year of birth in such a way that workers born between 1951 and 1955 can be observed in the age intervals 25-29 year-old to 61-64 years old, while workers born between 1986 and 1990 can only be observed when 25 to 29 years old. Each cohort can be observed when 25 to 29 year-old. Among workers belonging to this age group, figure 3.5 shows clearly that the share of salaried long-hours employees rose steadily between 1980 and 1995 and declined thereafter. A similar pattern can be observed between from 1985 on for workers of 30 to 34 years of age, and from 1990 on for workers being 35 to 40 years of age. Hence, the decline in the share of young employees working long-hours among Gen-X and Millennial workers relative to their Baby-Boom counterparts strongly contributed to the overall decline in long-workweeks observed after the mid-1990s.

Figure 3.5 also highlights another interesting pattern. For cohorts of workers born between 1951 and 1965 and belonging to the baby-boom generation, the life-cycle changes in the likelihood of working long hours are in line with standard models of life-cycle labor supply suggesting that workers increase the supply of work hours until middle-aged and decrease it later on. For workers belonging to the Gen-X and Millennial cohorts, instead, the likelihood of working long-hours does not appear to increase with age.

3.2.5 Long-Run Trends in Overtime Work: Intensive and Extensive Margins

I now show that long-run trends in the incidence of overtime work in the United States are mostly explained by changes in the share of salaried employees working long hours. Conditional on working full time, instead, the average weekly hours worked by long-hours employees did not change considerably between the 1980s and the 2010s.

In order to show that the rise and decline in overtime work were determined by extensive-margins changes in the share of long-hours salaried employees, I decompose the age and education -specific changes in average usual weekly work-hours occurred between the mid-1980s and the mid-1990s, and between the mid-1990s and the mid-2010s. Changes in average hours worked can be decomposed in two parts. The first part (first two lines of equation 3.2) captures the contribution to the change in work hours due to an increase or decrease in the share of overtime employees (Extensive Margin). The second part (third and fourth line of equation 3.2) show the contribution to the change in work hours due to an increase or decrease in work hours among overtime workers (usually working more than 48 hours per week) and among straight-time workers (usually working between 30 and 48 hours per week), keeping the share of overtime and straight-time workers constant.

Specifically, for each age group a in a specific education category e and straight time defined as weekly hours, h, not exceeding $x = 48$, the expected value of weekly hours worked in year t is

$$E_t^{a,e}(h) = Pr_t^{a,e}(h > x)E_t^{a,e}(h|h > x) + Pr_t^{a,e}(h \leq x)E_t^{a,e}(h|h \leq x) \tag{3.1}$$

The overall change in the mean of weekly hours worked between t and $t + \Delta$ can be decomposed as

$$\begin{aligned}
\Delta_h = E_{t+\Delta}^{a,e}(h) - E_t^{a,e}(h) = {} & [Pr_{t+\Delta}^{a,e}(h > x) - Pr_t^{a,e}(h > x)]E_{t+\Delta}^{a,e}(h|h > x) + \\
& + [Pr_{t+\Delta}^{a,e}(h \leq x) - Pr_t^{a,e}(h \leq x)]E_{t+\Delta}^{a,e}(h|h \leq x) + \\
& + Pr_t^{a,e}(h > x)[E_{t+\Delta}^{a,e}(h|h > x) - E_t^{a,e}(h|h > x)] + \\
& + Pr_t^{a,e}(h \leq x)[E_{t+\Delta}^{a,e}(h|h \leq x) - E_t^{a,e}(h|h \leq x)]
\end{aligned} \tag{3.2}$$

I perform the decomposition by comparing the observed change in mean weekly hours to the counterfactual change that would have been observed in the same education-age group if the shares of overtime and straight-time employees within each group were fixed at their time t level and the average hours worked by each category were fixed at their $t + \Delta$ level.

The results of the decomposition are reported in table 3.2 and show that both the rise and fall in weekly work hours can be entirely explained by long-run extensive-margin changes in the share of employees usually working long workweeks.[5] This result is not a mechanical outcome of the mass of full-time employees working exactly 40 hours per week. As figure 3.6 shows, average work hours did not systematically change over the last four decades among employees typically working overtime either.

The main stylized facts that I highlight in this section can be summarizd as follows: the rising trend in the incidence of long workweeks observed between the end of the 1970s and the 1990s and discussed in the literature (Kuhn & Lozano 2008, Michelacci & Pijoan-Mas 2011) entirely reversed by 2018. The reversed U-shaped trend in overtime work was determined by the rise and fall in the share of young, salaried employees working overtime. [6]

[5] Alternatively, the decomposition can be performed by comparing the observed change in mean weekly hours to the counterfactual change that would have been observed if the shares of overtime and straight-time employees were fixed at their time $t + \Delta$ level and the average hours worked by each category were fixed at their t level (Alternative Counterfactual). Table 3.2 shows that irrespective of the counterfactual exercise performed, extensive margin changes in the shares of overtime and straight-time employees determined the bulk of the observed increase and decrease in work hours.

[6] In Appendix section C.2 I show that long-run trends in the incidence of overtime work are not a mechanic outcome of changes in the composition of the workforce and of changes in the organization of work. First, I rule out that changes in the sex-composition of the workforce determined the trends in work hours and in the share of long-hours employees among male workers. Although female labor force participation steadily rose until the 1990s, but only slightly changed between the 1990s and the 2010s (Blau & Kahn 2013), in appendix figures C.1 and C.2 I show that trends in long hours among salaried women of different age groups are similar, though considerably less pronounced, to the observed trends for men. Second, in appendix figure C.3 I show that the rise and fall in long hours are observed for both married and unmarried men, thus not resulting from long-run changes in gender roles and in the within-household division of work. Finally, in appendix figures C.4 and C.5 I use CPS data from 1994 to 2018 to show that long-run trends in overtime work observed between the 1980s and the 2010s were not driven by changes in the share of employees working more than one job. Specifically, figure C.4 shows that the share of full-time employees working more than one job declined between the 1990s and the 2010s across and within education groups. In addition, C.5 shows that the share of employees working long hours on their main job declined from the mid-1990s for workers employed in one job and for workers holding multiple jobs, both across and within education groups. This evidence reduces

3.2.6 Long Work-Weeks Across and Within Occupations

Workers' salary status is associated with white-collar, often highly educated workers performing professional and executive jobs and/or having supervisory and managerial roles (Hamermesh 2002). The US Department of Labor also implicitly defines salaried workers as those who manage, organize and direct firms' operations at different levels.[7] It is then unsurprising that salaried workers tend to be mostly represented in professional occupations (including executive and managerial occupations) and among white collar workers such as teachers, social workers, administrative assistants, sale workers and technicians. These facts are shown in panel (a) of table 3.3.[8]

Table 3.3 also shows that, over the last four decades, the share of workers in professional occupations rose, and especially so among college graduate workers (panel (b)), while the share of workers in white collar occupations, typically in the middle of the wage distribution, fell. Among workers without a college degree, the share of blue collar employees rose over time (panel (c)). Overall, the pattern is consistent with well-studied trends towards employment polarization in the structure of occupations that occurred over the last four decades (Acemoglu & Autor 2011, Autor, Katz & Kearney 2006).

The transformations in the occupation structure, however, did not automatically determine the observed rise and fall in the incidence of long workweeks. In other words, overtime work did not rise at the end of the 20th century because the employment shares of occupations typically requiring long hours increased.

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concerns that long-run trends in the incidence of overtime work were driven by changes in the US employment structure and by the rise of the gig-economy.

[7] The DOL specifies that executives' main duties involve "managing the enterprise" or a "department or subdivision" of it, directing "the work of other full-time employees", and that executives "have the authority to hire or fire other employees", and decide "promotions or other change of status". Professionals perform mostly intellectual work "requiring advanced knowledge" and "discretion". Administratives perform work "directly related to the management or general business operations of the employer" (U.S. Department of Labor, Wage and Hour Division, Fact Sheet 17A).

[8] Given the types of jobs that salaried workers perform, the share of college graduates among salaried employees is higher than their share in the labor force as a whole. About 45% of salaried workers were college graduates around 1984, while 56% of them had a college degree in 2014.

Furthermore, movements of workers across occupations did not determine the subsequent fall in the incidence of long workweeks. As table 3.4 shows, between 1984 and 2014 the share of long hours employees rose and fell within all occupation classes. For all occupations and all education groups, the incidence of long workweeks peaked in the mid-1990s.

Further evidence that changes in the occupation structure did not mechanically drive long-run changes in the incidence of long workweeks is reported in figure 3.8. The figure shows the percentage-point change in the share of long-hours salaried employees occurred between 1983 and every subsequent year until 2018 (solid black line). The dashed black line shows the counterfactual change in the incidence of long workweeks obtained by keeping the education distribution and the distribution of workers of each education level across occupations at their 1983 level. The difference between the two lines is a raw measure of the portion of the change in the incidence of long work-hours that can be explained by changes in the education composition of the workforce and by transformations in the occupation structure. Arguably, the constant-composition pattern in the share of long-hours employees is highly similar to its observed time trend.

When keeping constant the share of professional employees working long hours (square-marked gray line), instead, the hump-shaped trend in the share of long-hours employees considerably flattens. In fact, around 60% of the rise and fall in the incidence of long workweeks are explained by the increase and decrease in the share of long-hours employees among professionals. Finally, 20% of the rise and fall in the incidence of long workweeks are explained by the increase and decrease in the share of long-hours white collar employees (triangle-marked black line).

It is worth noting that the strong contribution of professional workers to the rise and fall in overtime work is due both to the large share of professionals among salaried employees and to the fact that trends in overtime work are the most pronounced among professional workers.[9]

I provide further evidence that trends in the share of employees working long hours were determined by shifts in the incidence of long work-weeks within occupations by using a shift-share decomposition of approximatively twenty-year interval changes in the overall share of long-hours salaried employees.

Specifically, I decompose two-decade changes in overtime incidence among salaried full-time employees as follows. For salaried workers belonging to a given age category in a given year, I define $S^o_t = \frac{H^o_t}{H_t}$ the total (weighted) number of employees working long-hours in a representative week in year t. $S_{ct} = \frac{H_{ct}}{H_t}$ is the share employees working in 2-digit occupation c in year t; $S_{jct} = \frac{H_{jct}}{H_{ct}}$ is the share of c-occupation employees working in 3-digit occupation j in year t. $\gamma_{jct} = \frac{H^o_{jct}}{H_{jct}}$ represents the share of j-occupation employees working long hours in year t. Finally, λ^o_c, S_c, γ^o_c, S_{jc} are weights. The change in overtime incidence among salaried employees of a given age in a typical week between years 0 and t, Δ^o_t is

$$\begin{aligned}
\Delta^o_t &= S^o_t - S^o_0 \\
&= \sum_c \lambda^o_c \Delta S_{ct} + \sum_c S_c \left[\sum_j \gamma^o_j \Delta S_{jct} + \sum_j \Delta \gamma^o_{jt} S_{jc} \right] \\
&= \underbrace{\sum_c \lambda^o_c \Delta S_{ct}}_{\text{(a) Between c}} + \underbrace{\sum_c S_c \times \sum_j \gamma^o_j \Delta S_{jct}}_{\text{(b) Within c, Between j}} + \underbrace{\sum_c S_c \times \sum_j \Delta \gamma^o_{jt} S_{jc}}_{\text{(c) Within c, Within j}} \qquad (3.3)
\end{aligned}$$

This decomposition methodology is based on Olivetti & Petrongolo (2016) and Ngai & Petrongolo (2017) contributions.[10] I adopt and extend to the 2010 Census

[9] In the Appendix, I report two figures that replicate figure 3.8 by level of education. The figures show that changes in the incidence of long hours among professionals explain 80% of the change in overtime work among college graduates, and around one-third of the hump-shaped overtime work trends among workers without a college degree. Around 27% of workers without a college degree were employed in professional occupations between 1984 and 2014, while more than 40% of them were in blue collar occupations. Hence the equal contribution of all occupation classes to the trends in overtime among workers without a college degree shows that overtime rose and fell the most among professionals.

[10] The authors use an across-within industry shift-share decomposition to document secular changes in women's work hours.

classification the occupation classification proposed by Dorn (2009) and based on Meyer & Osborne (2005).

Equation 3.3 shows that changes over time in the share of salaried employees working overtime can be decomposed in three components. The first component, labeled (a) in equation 3.3, represents the portion of the overall change share of long-hours employees that is explained by shifts over time in employment across 2-digit occupation categories. The second component, labeled (b), captures the change in the incidence of overtime work explained by shifts in employment across 3-digit occupation categories within 2-digit occupation classes. The last component, labeled (c), measures the long-run changes in the incidence of overtime work explained by changes in the share of employees working long hours within 3-digit occupation groups.

The decomposition in equation 3.3 allows to understand the extent to which long-run trends in the incidence of overtime work are explained by aggregate changes in the structure of occupations, driving employment in and out of occupations that typically require overtime (a and b), and the extent to which trends are explained by within-occupations shifts in the incidence of overtime work. I perform the shift share decomposition of overtime incidence over two periods: 1979-1982 to 1995-1998, and and 1995-1998 to 2015-2018.

I report the results of the decomposition in table 3.5. Columns (2), (3) and (4) of table 3.5 report percentage-points changes in the share of employees working long hours explained by components (a), (b) and (c) of equation 3.3, respectively. The table provides neat evidence that changes in the occupation structure did not determine changes in the share of long-hours employees. In the first column, the table shows the percentage-point change in the share of long-hours salaried employees between the selected years reported in the corresponding row. The second column in the table shows the corresponding change in the incidence of long hours due to shifts in employment across 1-digit occupation classes. The third column shows the change due to shifts in employment within 1-digit occupation classes and across 3-digit occupations. The fourth column shows the change due to an increase or decrease in the share of long-hours employees within 3-digit occupations. As the last column in table 3.5 shows, secular changes in the shares of long-hours employees were almost entirely due to the rise and fall in the share of long-hours employees occurred within finely defined occupation groups. Shifts in employment across occupations, instead, did not strongly contribute to the trends.

While the incidence of long hours changed over the last four decades due to changes in the shares of long-hours employees within occupations, it did not change at the same rate across occupations. In order to understand which occupations were mostly impacted by changes in overtime work, I rank 3-digit occupations into quintiles according to the occupation-specific mean (log) wage in 1983-1986. For each occupation I then compute the change in the share of long-hours employees occurred between 1983-86 and 1995-98, and between 1995-98 and 2015-18. Finally, I regress the change in the share of long-hours employees on the quintiles dummies.

Figure 3.9 reports the results of this exercise. In particular, it shows the predicted change in the incidence of long hours by quintiles of the 1980s (log) wage distribution of 3-digit occupations, and the 95% confidence interval of the prediction, between 1983-86 and 1995-98 (black triangles), and between 1995-98 and 2015-18 (gray circles).

As the figure shows, the incidence of long workweeks increased between the 1980s and 1990s throughout the economy. At the same time, the rise in the share of salaried employees working more than 48 hours per week primarily involved occupations at the very top of the 1980s wage distribution. In particular, within the 5th quintile of the 1980s wage distribution, the occupations that experienced the largest increase in the incidence of long hours between the 1980s and the 1990s include executives, financial and HR managers, engineers, mathematicians, social scientists, lawyers and judges. This finding corroborates the evidence that changes in the incidence of long hours predominantly involved professional workers. Since the end of the 1990s, the share of long-hours workers also fell for most occupations, but the greatest drop was concentrated among workers at the fifth quintile of the 1980s occupation-wage distribution.

To summarize, work hours and the share of long-hours employees rose between the 1980s and the 1990s and steadily declined between the 1990s and the 2010s. Both trends were mostly due to within-occupation changes in the incidence of long workweeks, primarily involving young, professional workers in high-pay jobs.

3.3 The Rise and Fall in Returns to Working Long Hours

The facts that I documented in section 3.2, namely the long-run reversed-U shaped trend in the share of employees working overtime, can be explained by secular changes in the returns to work long hours. In this section I use the theoretical framework developed by Gicheva (2013) to model salaried employees' choice to work long-hours, I highlight the model's main predictions and test them using PSID data.

3.3.1 The Model: Long Hours, Promotions and Wage Growth

A sketch of the model proposed by Gicheva (2013) is as follows.[11] Assume that workers live for two time periods $t = \{1, 2\}$, and there are two job types $j = \{1, 2\}$. All workers are equally productive in $t = 1$ and period 1 productivity, η_1, does not depend on work hours. Productivity in period 2, instead, is sensitive to hours worked by worker i in the previous period. Specifically, $t = 2$ productivity is $\eta_2 = \eta_1(1 + \theta_i h_1)$, where θ_i denotes worker i's ability to learn from experience in period 1, and h_1 denotes the hours worked by i in period 1.

Workers' hourly output in job j in year t is $Y_{ijt} = d_j + c_j\eta_{it}$, where $0 < c_1 < c_2$

[11] I summarize the model and highlight its main predictions in this section. A full explanation of the model can be found in Gicheva (2010, 2013). I provide some derivations in Appendix section C.4.

and $0 < d_2 < d1$. Hence workers' hourly output responds more strongly to work hours in job 2.

Assume that all workers' start their two-period career in job-type 1, but careers can follow two different paths: in the "no-promotion" path, workers remain in job-type 1 for both periods 1 and 2; in the "promotion path" workers get promoted to job-type 2 in period 2.

Workers maximize their life-time utility, which takes the following form

$$U = \left(w_{i1}h_{i1} - b_i h_{i1}^2\right) + \left(w_{i2}h_{i2} - b_i h_{i2}^2\right) \tag{3.4}$$

Where b_i, denoting worker i's preferences for leisure, is assumed to be independent of worker i's learning ability θ_i.

The labor market is competitive and firms observe b_i, and η_{it}, so that each worker's hourly wage corresponds to their hourly productivity $w_{it} = d_j + c_j\eta_{it}$.

Workers make two choices: first, they choose the optimal amount of work hours in $t = 1$ and $t = 2$ conditional on being on the "no-promotion" career path or on the "promotion" career path. Second, they maximize their indirect life-time utility by choosing whether to follow the "no-promotion" path or the "promotion" path.

Workers' optimal choice of work hours is as follows. On the "no-promotion" path workers choose to work the same number of hours in both time periods 1 and 2, and

$$h_1^{n*} = h_2^{n*} = \frac{d_1 + c_1\eta_1}{2b_1 - c_1\eta_1\theta_1} \tag{3.5}$$

On the "promotion" path, employees optimally choose

$$h_1^{p*} = \frac{2b_i\left(d_1 + c_1\eta_1\right) + c_2\eta_1\theta_i\left(d_2 + c_2\eta_1\right)}{\left(4b_i^2 - c_2^2\eta_1^2\theta_i^2\right)} \tag{3.6}$$

$$h_2^{p*} = \frac{2b_i\left(d_2 + c_2\eta_1\right) + c_2\eta_1\theta_i\left(d_1 + c_1\eta_1\right)}{\left(4b_i^2 - c_2^2\eta_1^2\theta_i^2\right)} \tag{3.7}$$

In each period and on each career-path workers' optimally choose $h^*_{it} > 0$ assuming $2b_i > c_2\eta_1\theta_i$.

Conditional on the optimal choice of work-hours, each employee i determines whether to be on the "promotion" path or not. Specifically, i will select themselves on the "promotion" path if

$$V^p(w_1^p, w_2^p) \geq V^n(w_1^n, w_2^n) \tag{3.8}$$

For each level of workers' ability to learn θ_i, there is a threshold $\bar{b}(\theta_i)$ such that all workers with sufficiently weak preferences for leisure, $b_i \leq \bar{b}(\theta_i)$, select on the promotion path, while all workers with strong preferences for leisure, $b_i > \bar{b}(\theta_i)$, select on the "no-promotion" path. The threshold takes the following form

$$\bar{b}(\theta_i) = \frac{\left(c_2\left[(d_2 + c_2\eta_1) - (d_1 + c_1\eta_1)\right]^2 + \sqrt{\Delta(\eta_1, c_1, c_2, d_1, d_2)}\right)\eta_1\theta_i}{4\left[(d_2 + c_2\eta_1)^2 - (d_1 + c_1\eta_1)^2\right]} \tag{3.9}$$

The unique $\bar{b}(\theta_i)$ threshold and employers' ability to observe workers' types and choices ensure that all workers such that $b_i \leq \bar{b}(\theta_i)$ select into promotion career paths and are promoted in period two.

3.3.2 The Implications of the Model

I report in this subsection the main implications of the model. Proofs of the propositions listed below can be found in Appendix section C.4.

(1) $h_1^{*p} > h_1^{*n}$. Young employees on "promotion" career paths work longer hours than young employees on "no promotion" career paths. This outcome occurs as period 2 wage is more responsive to period 1 work-hours in careers that involve promotions to higher-responsibility roles ($c_2 > c_1$).

(2) $h_2^{*p} > h_1^{*p}$. Conditional on θ_i, workers on promotion paths work longer hours in period 2 than in period 1. Once promoted, workers in these careers experience the marginal productivity and wage gains of having worked long hours in period 1. These gains motivate workers to supply even longer hours in the second period of their life.

(3) $\frac{\Delta w^p}{w_1^p} > \frac{\Delta w^n}{w_1^n}$. Conditional on workers' ability to learn, θ_i workers on the promotion path experience faster wage growth than workers on career paths that do not involve promotions. Workers on career paths work longer hours in period 1 than workers in careers that do not involve promotions. This ensures that a promotion-path worker is more productive in period 2 than a worker on a "no promotion" path. In addition, as $c_2 > c_1$, wages respond more strongly to past work-hours for workers who are promoted to job $j = 2$ in period 2.

(4) $\frac{\partial\left[\Delta w^p/w_1^p\right]}{\partial h_{i1}} > \frac{\partial\left[\Delta w^n/w_1^n\right]}{\partial h_{i1}}$ and $\frac{\partial \Delta w^p}{\partial h_{i1}} > \frac{\partial \Delta w^n}{\partial h_{i1}}$. Wage growth experienced by workers on promotion paths respond more strongly to past work hours than wage growth experienced by workers on the "no promotion" career path.

(5) Since $\frac{\partial \Delta w^p}{\partial h_{i1}} = \theta_i c_2 \eta_1$ and $\frac{\partial \Delta w^n}{\partial h_{i1}} = \theta_i c_1 \eta_1$, any shock that increases (decreases) c_2 causes the sensitiveness of wage growth experienced by type θ_i workers to increase (decrease) among promotion-path employees.

(6) $\bar{b}(\theta_i)$ is a linearly increasing function of θ_i. Hence, all else equal, workers with strongest ability to learn on the job are more likely to select into promotion career paths. As they learn faster on the job in period 1, workers with higher θ_i experience faster wage growth in period 2 which enables them to select into promotion career path in spite of higher distaste for work hours b_i.

(7) $\frac{\partial \bar{b}(\theta_1)}{\partial d_2} > 0$ and $\frac{\partial \bar{b}(\theta_1)}{\partial c_2} > 0$. Conditional on θ_i, any shock that increases (decrease) in the wage gains experienced by workers who get promoted, determines a rise (fall) in the maximum distaste for work hours $\bar{b}(\theta_i)$ such that a type-θ_i worker selects into a promotion career path. As a consequence, the share of employees in long-hours jobs involving promotions increases as the wage gains from working long hours increase. Conversely, a fall in the returns to work long-hours determine a fall in the share of employees selecting into long-hours promotion career paths.

(8) $\frac{\partial^2 \bar{b}(\theta_1)}{\partial d_2 \partial \theta_i} > 0$ and $\frac{\partial^2 \bar{b}(\theta_1)}{\partial c_2 \partial \theta_i} > 0$. The share of employees selecting into promotion career-paths and working long hours increases faster among workers with high ability to learn θ_i as the dynamic wage gains from working long hours rise. This occurs as workers with high θ_i are more able to learn on the job in the first period of their life, $t = 1$. As a consequence, they can extract higher wage gains in period $t = 2$ that compensate them for higher levels of distaste for work hours b_i.

(9) As d_2 or c_2 increase and more workers select into promotion career paths, there are two countervailing effects on average work hours on promotion career paths. First, given θ_i and b_i, a worker on the promotion path optimally choose to work longer hours. That is $\frac{\partial h_{it}^{*p}}{\partial d_2} > 0$ and $\frac{\partial h_{it}^{*p}}{\partial c_2} > 0$ for $t = \{1, 2\}$. This effect tends to generate an increase in average work hours on promotion career paths. Second, a higher share of workers with relatively low ability to learn θ_i and, for each θ_i, a higher share of workers with relatively strong distaste for work hours, b_i select into promotion career paths. Since $\frac{\partial h_{it}^{p*}}{\partial \theta_i} < 0$ and $\frac{\partial h_{it}^{p*}}{\partial b_i} < 0$, this selection effect tends to reduce the average work hours on promotion career paths as d_2 or c_2 increase. As the two effects counteract each other, shocks that increase the dynamic returns of working longer hours may neither increase nor decrease average work hours on promotion career paths.

3.3.3 The Implications of the Model and the Data

The implications of the Gicheva (2013) model are broadly consistent with the stylized facts that I documented in section 3.2.

First, the 1980s-1990s rise in the share of American employees working overtime and the subsequent fall occurred between the mid-1990s and the 2010s are consistent with a secular increase and decrease in the life-cycle wage gains that long-yours employees benefit from (implication (7)) of the model).

Second, the model helps rationalize why long-run trends in the incidence of long hours are evident for salaried employees but not for hourly-paid employees. Under the Fair Labor Standards Act of 1938 and subsequent revisions, most salaried American employees are exempt from receiving hourly-wage bonuses when working more than 40 hours per weak (Whittaker 2003, 2005). It implies that salaried employees are more likely than hourly-paid employees to ground their decision to work long hours based on the life-cycle wage gains they expect to obtain rather than on current wage gains from overtime work. This is further emphasized by the fact that salaried employees tend to work in professional, managerial and executive jobs (Hamermesh 2002) that may involve steep wage-growth prospects over workers' life-cycle based on their past performance (Lemieux, MacLeod & Parent 2009, Piketty & Saez 2003).

Third, the model is consistent with the evidence that long-run trends in the share of overtime employees are mostly evident for relatively young workers. As Gicheva (2010, 2013) notices, workers' ability to learn may decrease as workers' age. If so, elder workers should be less likely than younger workers to select into promotion career path and they should be less responsive than young workers to changes in the dynamic returns to long-hours, d_2 and c_2. These facts are evident in the data. Figures 3.7 and 3.4 show that long-run trends in the likelihood of working long hours are mostly evident among relatively young workers, a fact that is further highlighted in figure 3.5.

Finally, the observation that average work hours have remained roughly constant over the last four decades among employees who usually work more than 40 hours per week is consistent with model implication (9): an increase (decrease) in the promotion career wage premium causes workers to rise their work hours conditional on their ability θ_i and taste for leisure b_i while attracting into promotion career-paths a higher share of workers with relatively low ability θ_i and strong tastes for leisure b_i, the latter typically choosing to work shorter hours.

3.3.4 Testing the Model: Wage Growth and Past Work Hours

At least two implications of the model can be directly tested in the data. Specifically, one can use panel data on individual employees to test whether the sensitiveness of wage growth to past work hours changed over the last four decades consistently with the predictions of the model.

As model predictions (4) and (5) state, since

$$\frac{\partial \Delta w^p}{\partial h_{i1}} = \theta_i c_2 \eta_1 \text{ and } \frac{\partial \Delta w^n}{\partial h_{i1}} = \theta_i c_1 \eta_1 \tag{3.10}$$

two facts should be observed in the data

1. Wage growth should be more strongly related to past work hours for employees on promotion career paths.
2. The relation between past work hours and wage growth should increase as c_2 increase and fall as c_2 decrease for workers on promotion paths but not for workers on "no promotion" paths.

If changes in the responsiveness of promotion career path wages contributed to the trends in the likelihood of working long hours observed in the data the following results should occur

1. The relation between wage growth and past work hours strengthened between the mid-1980s and the mid-1990s relative to earlier periods, while the relation between wage growth and past work hours weakened between the mid-1990s and the 2010s relative to earlier periods.
2. The relation between wage growth and past work hours should be systematically stronger for workers paid on a salary basis than for workers paid on a hourly basis.

3. The rise and fall in the relation between wage growth and past work hours should be evident for salaried employees but not for hourly-paid employees.

4. Among employees that are usually paid on a salary basis, the relation between wage growth and past hours should be systematically higher for employees who work long hours when young.

5. Among employees that are usually paid on a salary basis, the rise and fall in the relation between wage growth and past work hours should be evident for employees who work long hours when young but not for employees who do not work long hours when young.

In other words, if the implications of the model are correct, workers who are not paid by the hour and, among the latter category, workers who work long hours when young should be on a promotion career path. If so, these workers should experience faster wage growth over their life-cycle and the wage growth they experience should depend more strongly on past work hours relative to employees who typically work at most around 40 hours per week when young. Furthermore, for employees who work long-hours when young only one should observe an increase in the relation between wage growth and hours between the 1980s and the 1990s and a subsequent fall in the relation between the mid-1990s and the 2010s.

I test these two implications using PSID data between 1979 and 2018. For each worker i, I define $t = 1$ as the time period where i is between 25 and 29 years old, and $t = 2$ as the time period where i is between 30 and 34 years old. I only retain workers that can be observed at least once in $t = 1$ and in $t = 2$. h_{i1} are the weekly hours worked by i, on average, in $t = 1$, while Δw is the difference between the average hourly pay earned by i when 30 to 34 years old and the average hourly pay earned by i when 25 to 29 years old. I split workers in four cohorts according to whether they turn 25 years old by 1985 (cohort $c = 1$), between 1986 and 1995 (cohort 2), between 1996 and 2005 (cohort 3) or between 2006 and 2015 (cohort 4). I estimate the following regression model

$$\Delta w_{i,c} = \sum_{c=1}^{4} \gamma_c h_{i,c,1} + \beta' \mathbf{x}_{ic} + \varepsilon_{ic} \tag{3.11}$$

Where $\mathbf{x}_{ic}$ is a vector of control variables including indicator variables for whether a worker is a college graduate, for whether a worker is mostly observed in salaried jobs over time, for whether an employees works long hours (more than 41 hours per week) on average when 25 to 29 years old, dummy variables for the cohort a worker belongs to and interaction between the college and cohort dummy.

Table 3.6 reports the results of this exercise, which largely confirm the predictions of the model. First, column (1) shows that the relation between 5-years wage growth and past work hours has increased between the 1980s and the 1990s, while it has declined in magnitude and significance in the subsequent decades. Second, as reported in columns (2) and (3), the 1980s-1990s rise and 2000s-2010s fall in the strength of the relation between wage growth and past work hours has been entirely driven by salaried workers (column 2). For hourly paid workers, instead, the relation between wage growth and past work hours has not changed over the last four decades, and it has remained small in magnitude and statistically not significant. Third, as columns (4) and (5) shows, the relation between wage growth and hours tends to be stronger for salaried employees who work at least 41 hours per week on average when young (i.e. employees on a promotion career path) than for employees who work less than 41 hours per week (i.e. employees on a "no promotion" career path). For the former category of workers only the relation between wage growth and past work hours has been increasing in magnitude and remained statistically significant between the 1980s and the 1990s while it has declined and lost its statistical significance in the 2000s and 2010s. Finally, as shown in columns (6) and (7), the same results hold when extending the definition of salaried worker to any worker who is not paid by the hour.

It is worth noting that the results in table 3.6 are not driven by sample selection or by the time-interval considered in constructing wage growth for any worker. As table 3.7 shows, the estimation of regression 3.11 confirms the implications of the model also when I define wage growth as the difference between the average hourly pay obtained by a worker when 35 to 39 years old and the average hourly pay obtained by a worker when 25 to 29.

To summarize, the relation between 5-year wage growth and past work hours and the relation between 10-year wage growth and past work hours was strong and statistically significant for young workers until the mid 1990s and not statistically significant later on. Both relations were large in magnitude and increasing between the 1980s and the 1990s and small in magnitude and decreasing in the two subsequent decades. These results support the idea that an increase in the wage gains obtained by employees working long hours have been increasing in the 1980s and 1990s and falling later on, explaining the corresponding surge and decline in the share of salaried employees usually working overtime.

3.3.5 Robustness: a More General Test

The exercise that I carried out in the previous section has two limitations. First, I construct wage growth for each worker using only two time periods which are sufficiently close to allow me to estimate the relation between wage growth and past work hours for the most recent cohorts of workers as well. Second, and as a consequence of the previous point, I estimate the relation between wage growth and past work hours through OLS on a cross section including one data-point per worker. Even assuming that all workers are identical in terms of ability to learn θ_i, the heterogeneity across workers in their tastes for leisure b_i makes work hours an endogenous variable in regression 3.11.

In order to show that the results I obtain are robust, and that the relation between wage growth and hours did increase in the 1980s and 1990s and fell later on, in this section I estimate a more general model. Specifically, I regress the log-wage growth experienced by workers between any two time periods t and $t-1$ on past work hours in $t-1$ and on a set of control variables. This specification leverages the panel dimension of my data and allows me to perform a fixed-effect estimation, the latter reducing concerns that the coefficients of work hours are biased by unobserved worker-specific tastes for leisure b_i.

Specifically, the regression I estimate in this section grounds on the following model. Assume that workers choose their current work hours depending on their current wages and on the wage growth they expect to obtain as a consequence of their labor supply decision. That is,

$$\log h(i,t) = a \log w(i,t) + \frac{\gamma}{n} \left[E(t)\beta^n \log w(i,t+n) - \log w(i,t)\right] \tag{3.12}$$

Assuming that workers expectations are rational, one can find a relation between current wages in year $(t+n)$ and past work-hours and wages that can be estimated through OLS.

$$\log w(i,t+n) = \varphi \log h(i,t) + \delta \log w(i,t) + \varepsilon(i,t+n) \tag{3.13}$$

Where $\varphi = \frac{n}{\gamma\beta^n}$, $\delta = \frac{1}{\beta^n}\left[1 - \frac{an}{\gamma}\right]$ and $\varepsilon(i,t+n)$ is a rational expectation error.

Assuming that workers are heterogeneous in their tastes for leisure, and that these tastes drive work hours choices and affect the wages workers earn, the relation between current wages in year $(t+n)$ and past work-hours can be estimated via a fixed effect estimation.

I estimate the equation above following the specification proposed by Bell & Freeman (2001) and estimated by Michelacci & Pijoan-Mas (2011) as well. Specifically, I let $n = 1$ and $\log w(i,t+1)$ be the logarithm of a worker's wage per hour in year $(t+1)$. In addition, i measure $\log h(i,t)$ and $\log w(i,t)$ as the logarithm of, respectively, average weekly hours worked, and hourly wage earned, by worker i in the five years between $(t-4)$ and t. I calculate hourly wages by dividing annual earnings in a certain year by the total number of weekly hours times annual weeks worked by an employee in the same year. I estimate the model above by restricting the sample to workers aged 25-55 years old and who are usually not self-employed.

I further restrict the sample to workers observed at least three times in a five-year time span before 1996 or observed at least three times in a ten-year time after 1996, when the PSID becomes biennial.

Following Michelacci & Pijoan-Mas (2011) I include controls for education, a quadratic function of age and their interactions with time, and I allow the impact of past hours on current wages to vary over decades. In particular, I allow φ to take different values in 1981-85, 1986-90, 1991-95, 1996-2000, 2001-05, 2006-10, 2011-15. Estimating φ to increase until 1996-2000 and decrease thereafter would suggest that the dynamic wage-premium for working long hours rose until the mid-1990s and fell in the first two decades of the 21th Century. Such movement in the premium for long-hours of work might explain the dynamic rise and fall in the share of employees working long-hours observed over the same period of time.

Table 3.8 reports the results of this exercise, which corroborate the results of the estimation of regression 3.11. Overall, the table provide evidence supporting the idea that the dynamic wage-premium experienced by workers when supplying longer hours consistently rose between the 1980s and the 1990s and fell later on. The coefficients estimating the relation between wage growth and hours are larger in magnitude and changed more sharply over the last four decades for salaried workers than for workers paid by the hours. Among salaried employees, the relation between wage growth and hours is especially strong, and changed the most over time for relatively young workers.[12]

To conclude, the evidence provided in this section broadly supports the hypothesis that the wage premia that workers obtain over their life-cycle when working long-hours have been increasing between the 1980s and the 1990s and declining later on. These trends in the wage premia can explain the reversed-U shaped trend

[12] Table C.2 in Appendix section C.5 shows that the results of the estimation are qualitatively unaffected when I include current work hours as a control variable in equation 3.13. Including this control variable, the specification of the regression model I estimate is identical to the one estimated by Michelacci & Pijoan-Mas (2011). As such, I can compare the coefficients I estimate with their results for the years in which the sample I consider overlaps with theirs. This allows me to check the credibility of my estimates in light of the existing literature.

in the share of salaried employees working long-hours observed over the last four decades.

3.4 The Relation Between Wage Inequality and Long Hours

In the Gicheva (2013) model, shocks to the life-cycle wage premia for working long hours also determine a change in the dispersion of the wage distribution. The larger wage gains workers obtain on "promotion" career paths when working long hours, the greater the wage gap between workers on "promotion" career paths and workers in "no-promotion" career paths, the more spread out the wage distribution becomes. As such, the Gicheva (2013) model predicts that the share of employees working long hours should be positively correlated with wage dispersion.

3.4.1 The Inequality Hours Hypothesis: Intuition and Evidence

Initially formulated by Bell & Freeman (2001), the inequality-hours hypothesis suggests that high wage dispersion fosters long work-hours. This relation may exist if wage dispersion proxies the distribution of future wage gains available to workers exerting work effort (Bell & Freeman 2001), consistently with the Gicheva (2013) model. If so, the inequality-hours hypothesis should be well suited to explain the high share of long-hours workers within high-pay professional occupations. As a matter of fact, these occupations are often characterized both by high-wages and by a high pay-growth rate over workers' life-cycle. In addition, work hours do impact wage growth in these occupations (Bertrand, Goldin & Katz 2010*b*).

Using CPS-ORG data, I show that the cross-sectional relation between wage inequality and work hours tends to support the inequality-hours hypothesis. Table 3.9 shows the results of cross-sectional regressions of (log) weekly work hours on the standard deviation of residual (log) hourly pay across 3-digit occupations in selected years. In line with the previous literature, all models control for the occupation-specific average (log) hourly pay, and include dummies for 1-digit occupation classes (Bell & Freeman 2001). The relation between inequality and hours is systematically positive and statistically significant, although it is strongly lower in magnitude in the 2010s relative to the previous decades.

Building on Bell & Freeman (2001) argument, Kuhn & Lozano (2008) and Michelacci & Pijoan-Mas (2011) suggest that the secular rise in inequality observed in the United States since the end of the 1970s may explain the contemporaneous surge in the share of employees working long-hours observed until the 1990s. If so, one should observe that wage dispersion increased the most between the 1980s and the mid-1990s within those occupations that experienced the strongest rise in the incidence of long workweeks. Figure 3.10 panel (a), however, shows that this is not the case.

The figure plots the change in the predicted share of long-hours salaried employees at different quintiles of the 1980s occupation-wage distribution between 1983-86 and 1995-98 (black triangles). In addition, the figure shows the corresponding predicted change in the standard deviation of residual wages across occupations (gray squares). Arguably, the rise in wage dispersion was not stronger at the top of the 1980s occupations-wage distribution. Panel (b) in figure 3.10 reports the same predictions for the time span 1995-98 to 2015-18. It shows that, although the incidence of long hours fell throughout the wage distribution, wage dispersion kept increasing. In particular, wage dispersion increased between the mid-1990s and the 2010s even among those occupations where the share of long-hours workers declined the most. The results in figure 3.10 are relevant, as they are not in line with findings that work hours increased the most between the 1980s and the mid-1990s within occupations whose wage dispersion increased (Kuhn & Lozano 2008, Michelacci & Pijoan-Mas 2011).

The lack of consistency between my findings and the previous literature is due to the difference in the selected time-intervals over which changes in wage inequality and hours are computed. Using CPS-ORG data, Kuhn & Lozano (2008) compare changes in hours and in residual wage dispersion between 1983-85 and 2000-02, while Michelacci & Pijoan-Mas (2011) use Census data and changes in hours and in residual inequality between 1980 and 2000. Yet, as I previously showed, the peak in the incidence of long-hours occurred around 1995. Hence, although more employees worked long-hours at the beginning of the 2000s relative to the beginning of the 1980s, by the beginning of the new century overtime work had already begun its decline. The fast increase in inequality that occurred in the United States during the second-half of the 1990s may have affected the inequality-hours relation found in the literature.

Consistently with the findings reported in figure 3.10, when I replicate Kuhn & Lozano (2008) analysis between 1983-86 (synthetic year 1984) and 1995-98 (synthetic year 1996), I find that the cross-occupations relation between changes in long hours and changes in wage dispersion is not statistically significant and, depending on the definition of wage dispersion used, negative. Furthermore, for all models the R^2 shows that variation in the rise in wage dispersion across occupation is not able to explain the cross-occupation variability in the rise in overtime work. The results are shown in table 3.10. When I replicate the Kuhn & Lozano (2008) analysis for the time span between 1996 and 2008, I find that the cross-occupational correlation between changes in wage dispersion and changes in overtime work are positive, large in magnitude and significant. The results, reported in table 3.11, suggest that the strong correlation between within-occupation changes in wage dispersion and within-occupation changes in overtime work that Kuhn & Lozano (2008) found, was strongly driven by the time frame they used in their analysis. By 2002, the last year in Kuhn & Lozano (2008) sample, however, overtime work had already been declining for at least six years.

The results I find are further supported when I run separate cross-occupation regressions by quintile of the 1983-86 cross-occupation wage distribution and by decades. The results of the regressions for the time-periods 1984 to 1990 (the Eighties) and 1990 to 1996 (mid-Nineties) are reported in figure 3.11. In all panels of figure 3.11, the graphs on the left-hand sides show that, between 1984 and 1990, overtime work increased in most 3-digit occupations at all quintiles of the wage distribution, irrespective of whether within-occupation wage dispersion was rising or falling in the same decade. This evidence is consistent with the finding that overtime work mostly increased during the Eighties. Across quintiles, however, the cross-occupation correlation between change in overtime and change in wage dispersion is not always positive. In addition, across all quintiles the R-Squared of the cross-occupational regressions are small, showing that cross-occupational variation in the rise in wage dispersion within occupations cannot explain the observed cross-sectional variation in the rise of overtime work. The results question whether the inequality-hours hypothesis can really explain the rise in overtime work observed over the eighties.

Furthermore, these findings are corroborated by the results of the cross occupational regressions for the time period 1990 to 1996, shown on the right-hand sides of all panels in figure 3.11. Over this time period, while overtime was mostly rising at the top of the wage distribution and for young college graduates, the cross-occupational correlation between change in wage dispersion and change in overtime work is almost always negative.

Figure 3.12 shows the results of the same regressions for the time periods 1996-2002 and 2002-2008. The left-hand side figures in all panels of figure 3.12 provide evidence of a positive cross-sectional correlation in the 1996-2002 period between changes in wage dispersion and changes in overtime work across occupations. The relation is particularly strong at the top of the wage distribution, where the cross-occupational variation in the 1996-2002 within-occupations change in wage dispersion explains 27% to 38% of the cross-occupational variation in the within-occupations change in the share of employees working long hours. During this period, however, overtime work among salaried employees has been declining in many 3-digit occupations, including those at the top of the wage distribution. It means that the positive relation between changes in wage dispersion and changes in overtime work in fact post-dates the surge in long hours observed between the 1980s and the mid-1990s. Finally, the figures on the right-hand side of all panels in figure 3.12 show that the cross-occupation relation between changes in overtime work and changes in wage dispersion was mostly small and not significant between 2002 and 2008, a time period when overtime work has kept declining within most 3-digit occupations.

Overall, these results question the validity of the inequality-hours hypothesis as a plausible explanation of the 1980s surge in overtime work. As a consequence, they also show that the same hypothesis may be inadequate to explain the reversal in the overtime-work long-run trend occurred in the mid-1990s. More specifically, the findings I show in this section cast doubts on the interpretation of overall wage dispersion as a proxy of the life-cycle wage gains that workers can expect to obtain by working long hours.

Long-run trends in residual wage dispersion provide further evidence showing that wage inequality may not be a suitable proxy to capture changes in the dynamic wage returns from working long hours that may have driven trends in overtime work. If trends in wage dispersion captured underlying trends in the wage premium from working long hours, one should expect trends in wage inequality to be consistent with the observed trends in the share of long hours employees. In other words, one should expect wage inequality to rise fast in the 1980s while flattening in the mid-1990s and declining later on. Wage dispersion, however, has been increasing over the last four decades.

Figure 3.13 shows the evolution of the variance of residual wages among CPS-ORG salaried workers between 1983 and 2018. The variance is computed separately for all workers (thick black line) and for professionals, white collar and blue collar workers. As the figure clearly shows, although inequality rose overall over the last four decades among all workers, it increased faster at the end of the

1990s and at the end of the 2010s. The time-trend in residual wage dispersion is instead flatter in the 1980s, when the strongest rise in overtime work occurred. When considering professional workers, who predominantly determined the overall changes in the incidence of long workweeks over the last forty years, it is clear that residual wage dispersion was almost identical in the mid-1990s to its level at the beginning of the 1980s. By 2001, instead, the residual wage variance among professional workers was more than 8% higher than it was in 1983.

Figure 3.13 also shows that wage dispersion did not decline after 2000s. In particular it did not decline among professional workers who are typically employed in high-pay jobs. This piece of evidence is consistent with the findings in figure 3.10. Although workers in high-pay jobs determined the bulk of the reversal in the overtime work trend, patterns in wage dispersion for these workers are not consistent with the inequality-hours hypothesis. Panels (a) and (b) of figure 3.14 further support this conclusion. They show how the gaps between percentiles of the residual wage distribution evolved over time among professional and white collar workers. The patterns in the 90-50 and 90-10 percentile gaps clearly indicate that pay inequality increased in the 2000s and 2010s.

The continuous rise in wage dispersion is not a unique feature of CPS-ORG data. In fact, residual pay inequality follows similar long-run trends in both CPS-ORG and PSID data. This piece of evidence is reported in figure 3.15.

The analyses I performed so far show that the inequality-hours hypothesis may not be able to explain long-run changes in the incidence of overtime work. Michelacci & Pijoan-Mas (2011), however, suggest that overall residual pay inequality may not be the correct measure capturing dispersion in wage growth opportunities across workers in different careers. Accordingly, Michelacci & Pijoan-Mas (2011) measure dispersion in the distribution of wage offers available to workers using the variance in residual wages among workers who are newly hired from unemployment.

I use PSID data to replicate their analysis and show that, even using the alternative measure of wage dispersion that Michelacci & Pijoan-Mas (2011) adopt, inequality does not appear to be declining in the 2000s and in the 2010s. The results of this exercise, reported in table 3.12, suggest that this alternative measure of wage dispersion may not be a suitable proxy for the dynamic wage returns of working long hours. If it was, one should observe inequality in wage offers received by workers to decline consistently with the decline in overtime work observed between the mid-1990s and the 2010s.

To conclude, and in-depth analysis of the relation between wage dispersion and overtime work suggests that, taken face value, the inequality-hours hypothesis may not be able to explain long-run trends in the share of employees working long hours. Specifically, the reduced-form evidence I provided in this section shows that:

1. Between the 1980s and the mid-1990s the share of overtime work has been rising. At the same time, different measures of wage dispersion have also been increasing. Yet, the cross-occupational relation between changes in within-occupation wage dispersion and changes in the within-occupation share of long-hours employees does not appear to be consistently positive and significant. This suggests that the observed rise in wage inequality observed between the 1980s and the mid-1990s may not predominantly reflect an increase in the life-cycle wage premium from working long hours.

2. Between the mid-1990s and the 2010s overtime work has been declining while different measures of wage dispersion have kept increasing. This evidence directly contradicts the hypothesis that, by reflecting changes in the life-cycle wage gains from working long-hours, trends in wage dispersion should drive trends in the share of employees working overtime.

3.4.2 Reframing the Inequality-Hours Hypothesis: Returns to Long Hours and Persistent Wage Dispersion

The evidence I provided in the previous section shows that neither changes in overall wage dispersion, nor changes in within-occupation wage dispersion or changes in the dispersion of the distribution of job offers that workers face can explain the long-run rise and fall in the share of employees working long hours. In principle, this evidence may have two implications. On the one hand, this evidence may suggest that the wage premia from working long hours have not changed over the last four decades, thus casting doubts on the robustness of the evidence I provided in sections 3.3.4 and 3.3.5. On the other hand, it may imply that the above-mentioned measures of wage inequality are not accurate measures of the life-cycle wage premia that employees can obtain when working long hours.

In this section I provide suggestive results that corroborate the evidence that the wage premia for working long hours have been increasing in the 1980s and 1990s and declining later on, while refining and substantially confirming the validity of the inequality-hours hypothesis.

In the framework of the Gicheva (2013) model, changes in returns from working long-hours determine changes in the wage difference across different careers, that is, in the average life-cycle wages between workers who pursue different career paths. As returns from long hours increase, wages grow faster over the life-cycle for employees working long hours when young. Consequently, their average life-cycle wage becomes higher relative to the average wage earned over the life-cycle by employees who do not usually work long hours. In other words, in the Gicheva (2013) model, shocks that affect the wage returns from working long hours affect the dispersion of permanent earnings, the latter being defined as the average life-cycle earnings that workers obtain over their life-cycle.

While changes in the wage gains from working long hours should determine changes in the dispersion of average life-cycle earnings, long-run trends in residual wage dispersion may reflect both changes the dispersion of permanent earnings and changes in the dispersion of transitory shocks to workers' wages. Gottschalk & Moffitt (1994, 1999, 2009) were the first to provide an in-depth analysis of long-run trends in the dispersion of permanent and transitory income shocks, and highlighted the need to distinguish between the two in order to understand the roots of long-run changes in income inequality. In particular, Gottschalk & Moffitt (1994, 1999, 2009) argue that while changes in labor demand potentially impacting wage premia should determine changes in permanent wage dispersion, trends in transitory wage dispersion should reflect underlying changes in job and employment instability, and provide evidence that the variance of transitory income shocks determined a vast portion of the increase in residual earnings dispersion observed in the US between the 1980s and the 1990s.[13] These results question the idea that most of the increase in residual wage dispersion observed between the 1980s and the 1990s can be attributed to an increase in the price of unobserved workers' skills (Juhn, Murphy & Pierce 1993), to skill-biased technological change (Autor & Katz 1999, Autor, Katz & Kearney 2006, 2008) or to other factors contributing to permanent wage dispersion.[14] If so, long-run trends in residual wage dispersion do not correspond to changes in persistent wage dispersion and, potentially, to changes in the returns to long hours. Hence, they are not suitable to test the inequality-hours hypothesis in the data.

Accounting for the contribution of Gottschalk & Moffitt (1994, 1999, 2009), Heathcote, Storesletten & Violante (2010) propose a model and an estimation technique that allow to separately identify the variance of permanent wage shocks and the variance of transitory wage shocks using panel data. Here I implement the method they propose on PSID data to estimate the 1980s-2010s trends in

[13]See also Violante (2002) for a theoretical analysis of the factors that may have contributed to the rise in earnings instability.

[14]A deep analysis of the range of possible impacts of technological change of different measures of inequality can be found in Hornstein, Krusell & Violante (2005). Lemieux (2006) provides some evidence that changes to the composition of the US labor force also contributed to the rising wage inequality observed in the United States between the 1970s and the end of the 1990s.

permanent and residual wage dispersion.[15][16]

The statistical model for wage residuals that Heathcote, Storesletten & Violante (2010) propose is as follows. Let $y_{i,j,t}$ be the residual from a mincerian wage regression for a worker i of age j in year t. $y_{i,j,t}$ can be decomposed as

$$y_{i,j,t} = \eta_{i,j,t} + \nu_{i,j,t} + \tilde{\nu}_{i,j,t} \tag{3.14}$$

Where $\eta_{i,j,t}$ is a persistent component to labor productivity, $\nu_{i,j,t}$ is a transitory worker-specific productivity shock and $\tilde{\nu}_{i,j,t}$ captures measurement error. $\nu_{i,j,t}$ is a random variable with mean 0 and variance λ^{v}, and $\tilde{\nu}_{i,j,t}$ is a random variable with mean 0 and variance $\lambda^{\tilde{\nu}_t}$. I follow Heathcote, Storesletten & Violante (2010) in assuming $\lambda^{\tilde{\nu}} = 0.02$ in PSID data.[17] The persistent component is assumed to follow an AR(1) process

$$\eta_{i,j,t} = \rho\eta_{i,j,t-1} + \omega_{i,j,t} \tag{3.15}$$

Where $\omega_{i,j,t}$ is a persistent individual productivity shock with mean 0 and variance λ_t^{ω} and the variance of $\eta_{i,1,t}$ is assumed to be constant over time and equal to λ^{η}. The latter assumption implies that there are no cohort-specific components changing the spread in the distribution of labor productivity. All components of residual wages are assumed to be orthogonal to each other and i.i.d. across the population. Under the additional assumption that, in $t = 1$ (year 1979 in the data I use) the distribution of productivity is in steady-state, the panel dimension of the data allows to use the variances of wage residuals among workers of age j in each year t and the auto-covariances between the wage residuals of workers of age j in year t and of age $j + k$ in year $t + k$ to identify the time-varying λ_t^{ν}

[15]See also Meghir & Pistaferri (2011) for an in-depth analysis of permanent and transitory wage dispersion.

[16]Gustavsson (2014) tests the inequality-hours hypothesis using longitudinal data from Sweden and separately estimates the variances of transitory and persistent wage shocks following Meghir & Pistaferri (2011) by industry. He then shows that there exists a positive cross-industry relation between the the variance of persistent wage shocks and the hours worked by employees, while transitory wage dispersion has no impact on work hours.

[17]This assumption grounds on evidence provided by French (2004)

(transitory wage shock variance) and λ_t^{ω} (persistent wage shock variance). The same moments also allow to identify the wage dispersion that workers encounter at labor market entry ($j = 1$), that is λ^{ν} and the autocorrelation coefficient ρ. I provide proof of identification and a more in-depth explanation of the estimation technique in Appendix section C.6.[18]

I estimate the model twice on two different sub-samples of PSID workers. First, I estimate the model on college graduate workers; second I estimate the model on workers who report to be paid on salary basis (i.e. not by the hour) most of the times in which they are observed in PSID data. I select observations according to these criteria for two reasons. First, salaried workers, most of whom are college graduates, drove the rise and fall in long-run trends in overtime work. Second, the stylized facts I showed in section 3.2 show that the share of employees working long hours did not change over the last forty years due to changes in the composition of the salaried workforce. This reduces concerns that part of the trends in persistent and transitory wage variance capture underlying unobserved changes in the distribution of ability within the population of interest.

Figures 3.16 and 3.17 report the main results of the exercise. Panel (a) of figure 3.16 shows the estimated pattern in variance of the transitory component of residual wages between 1979 and 2017 among college graduate workers. Panel (b) of the same figure shows the estimated pattern in the variance of the persistent component of residual wages in 1979-2017 among college graduate workers. Panels (a) and (b) of figure 3.17 show the estimated variances of transitory and persistent wage shocks among salaried employees.[19]

[18] Lochner, Park & Shin (2017) use PSID data from 1968 to 2013 to estimate a more general model that allows them to identify changes in the variance of transitory wage shocks and different components of the time-varying variance in persistent wage shocks due to, respectively, changing labor demand (e.g. changing returns to unobserved skills) and changing distribution of unobserved skills within the labor force. In the estimation I perform, I assume that the distribution of unobserved skills is constant over time across cohorts. This assumption grounds on the fact that I estimate trends in persistent and transitory wage variance on sub-samples of relatively homogeneous workers: college graduates, and workers paid on a salary basis.

[19] The estimated values of the autocorrelation coefficient ρ and of the time-constant $t = 1$ persistent wage shock are reported in table 3.13. For comparison, the same table also reports the values of the same parameters estimated between 1968 and 2001 on all male employees by Heathcote,

The figures highlight a number of interesting patterns. First, consider the time frame between 1979 and the mid-1990s, namely the time period work hours and the share of employees working long hours have been increasing for salaried workers. Figures 3.16 and 3.17 show that, over the same time period, the variance of transitory wage shocks and the variance of persistent wage shocks have been increasing among college graduates and among salaried employes alike. Yet, the bulk of the rising wage dispersion occurred during this time period was determined by an increase in income volatility, that is, by an increase in the variance of temporary wage shocks. The increase in the variance of transitory wage shocks between 1979 and the mid-1990s was almost two times larger than the contemporaneous increase in the variance of persistent wage shocks among both college graduates and all salaried employees. Second, consider the time frame between the mid-1990s and 2010. Over this time period, the variance of transitory wage shocks has kept increasing at an increasing rate relative to the previous fifteen years. Conversely, the variance of transitory wage shocks has been falling substantially among college graduate workers and among salaried workers over the same period of time. Finally, both transitory and permanent wage dispersion have been declining after 2010.

This evidence suggests two things. First, the bulk of the rise in residual wage dispersion occurred among salaried employees and among college graduates between the 1980s and the mid-1990s was determined by a secular increase in the variance of transitory wage shocks. These results, that broadly confirms previous findings by Gottschalk & Moffitt (1994, 1999, 2009) and by Heathcote, Storesletten & Violante (2010), also help rationalize the findings I provided in section 3.4 which did not show any evidence of a positive relation between changes in residual wage dispersion and changes in work hours over that period of time. Changes in overall residual wage dispersion between the 1980s and the mid-1990s are not a

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Storesletten & Violante (2010).

suitable proxy for changes in the wage premia from working long-hours, while they are likely to mostly reflect the strong increase in the dispersion of transitory wage shocks occurred during that time frame.

Second, the fact that the variance of transitory wage shocks kept increasing after the mid-1990s, and that the growth in the variance of transitory wage shocks between the mid-1990s and 2010 is much larger in magnitude than the fall in the variance of persistent wage shocks occurred over the same time period, explains that the rising wage dispersion observed in the 2000s entirely reflects changes in wage volatility. Hence, trends in overall wage dispersion cannot be used to test the relation between wage inequality and work hours consistent with the inequality-hours hypothesis.

Finally, and perhaps most importantly, the variance of persistent wage dispersion has been rising between the 1980s and the mid-1990s and falling later on, consistently with the timing of the reversal in the long-hours trends documented in section 3.2 and with the timing of the rise and fall in the relation between wage growth and work hours estimated in section 3.3.4. It is then plausible to suggest that persistent wage dispersion may capture, among other factors, the wage returns that workers obtain over their life-cycle from working long hours, and that a secular rise and fall in such wage premia might have contributed to the contemporaneous growth and decline in persistent wage inequality and in the share of employees working long-hours that I documented in this chapter.

3.4.3 Discussion: Inequality and Hours. Human Capital or Incentive Schemes?

The evidence provided in the previous section broadly supports the inequality-hours hypothesis initially proposed by Bell & Freeman (2001) and is consistent with the implications Gicheva (2013) model with wage premia for long-hours allowed to vary over time. In this model, learning-by-doing and human capital accumulation are the main mechanisms driving employees' decision to work long hours and to enter promotion career path. Workers who invest in longer hours when young become more productive later on in their life, and gain larger gains from their investment when entering careers that ensure promotions to higher-level positions.[20] In this framework, work hours are not used by firms as an incentive mechanism to discern workers' unobserved productivity and induce effort as in tournament models (Lazear & Rosen 1981) or in rat-race models (Landers, Rebitzer & Lowell 1996). While Bell & Freeman (2001) argue that turnament/incentive models may be better suited to explain the empirical relation between inequality and hours than human capital models, here I argue that turnament/incentive models cannot explain the 1980s-1990s rise and the 1999s-2010s fall (1) in the share of employees working overtime; (2) in the relation between wage growth and past work hours on promotion career paths; and (3) in the variance of persistent wage shocks.

Consider first the Lazear & Rosen (1981) tournament model. In this framework, workers' pay is linked to to their rank in a firm but not on their output level. Workers compete with each other to obtain a promotion to a higher-rank position. At labor market entry, workers choose their work hours to maximize the probability of being promoted to a higher rank and obtain a higher wage in the future. If all workers are identical in their preferences over work hours, all workers choose to work the same optimal number of hours to affect their promotion probability. Future expected wage levels, however, should not affect employees' optimal supply of work hours but just the decision to enter the promotion game. If so, there should not be a positive relationship between current wages and past work hours of the type I documented in section 3.3.5.

Consider now the Landers, Rebitzer & Lowell (1996) model. In this framework work hours are used as a screening mechanism to discern highly productive em-

[20] Using a search model where human capital accumulation affects the likelihood of receiving better job offers in the future, as in the framework proposed by Michelacci & Pijoan-Mas (2011) does not affect the main implications of the Gicheva (2013) model to the extent that human capital accumulation is transferable across jobs.

ployees who may deserve a promotion and a pay increase. As a consequence, an equilibrium occurs in which employees work inefficiently long hours in an attempt to elicit a promotion. While the model posits a relation between work hours, wage increases and promotion possibilities, the model also has the counterfactual implication that rising competition from potentially low-ability types of workers within occupations should drive an increase in average work hours. The share of workers in professional, managerial and executive jobs that often require long hours has been increasing between the 1980s and the 2010s (table 3.3). The rising competition for these jobs should have driven a consequent increase in work hours in these occupations if . Yet, after the mid-1990s the share of employees working long hours has been declining within these occupation classes (table 3.4).[21]

3.5 Conclusions

In this chapter, I documented that work hours have been rising in the 1980s and 1990s and falling later on, as a consequence of the secular changes in the share of employees typically working long hours. To the best of my knowledge, this fact had not yet been observed or documented. In my empirical characterization of the hump-shaped 4-decades trend in overtime work, I showed that its rise and fall were both determined by salaried employees, and in particular by relatively young workers and by workers employed in high-pay professional jobs.

I showed that the secular growth and decline in overtime work can be explained by a contemporaneous rise and fall in the life-cycle premia that employees supplying long hours can expect to obtain, consistently with a model where employees supply long work-hours to improve their productivity and get access to high-level positions that remunerate their acquired skills (Gicheva 2013).

[21] Rat-race models of the type proposed by Landers, Rebitzer & Lowell (1996) also require strict conditions for an equilibrium to occur. While these conditions may characterize certain types of occupations (e.g. lawyers), it is unlikely that they hold for the vast class of occupations and workers among which the likelihood of working long hours rose and fell over the last forty years.

Finally, I used the main implications of the (Gicheva 2013) model to test the inequality-hours hypothesis (Bell & Freeman 2001). I showed that permanent wage dispersion (Gottschalk & Moffitt 1994, 1999, 2009) has been growing between the 1980s and the 1990s and declining later on, consistently with an underlying rise and fall in the life-cycle wage premia for working long hours that might have driven both trends in persistent wage inequality and in overtime work.

Overall, this work contributes to our understanding of the roots of the long-run trends in work hours and overtime work, which affect our normative interpretation of secular changes in employment and labor supply. In fact, the results that I provided in this work suggest that the surge in overtime work occurred in the 1980s and 1990s may be as a signal of a dynamic labor market offering increasingly lucrative career opportunities to certain workers, while its subsequent decline could be suggesting that career opportunities declined in the 2000s and 2010s especially for young workers in salaried jobs. This fact would be consistent with findings that the "fortunes of the youth" have been declining in the new century (Beaudry, Green & Sand 2014), that the demand for high-pay cognitive jobs dropped over the same time period (Beaudry, Green & Sand 2016), that the college wage premiums has declined (Autor, Goldin & Katz 2020, Valletta 2016) and that the age wage gap has grown (Bianchi & Paradisi 2021). Conversely, the facts and findings I provide in this work question the hypothesis that, unrelated to its previous increase, the decline in work hours observed in the 2000s and 2010s was an outcome of a welfare-improving increase in the marginal value of leisure that affected the most recent cohorts of young workers (Aguiar, Bils, Charles & Hurst 2017).

While out of the scope of this chapter, in future work I will study the determinants of long-run changes in the wage premia from long-hours, and provide a quantitative analysis their impact on permanent wage dispersion and on work hours.

3.6 Tables

Table 3.1: The Contribution of Age Groups to the Change in the Incidence of Long Hours

	1983-87	1993-97	2003-07	2013-17
(1) Share Young Workers (25-44)	65.6	64.9	57.2	53.3
(2) Share Long Hours - 25-44 y.o.	27.6	34.1	29.0	24.5
(3) Share Long Hours - 45-64 y.o.	22.7	30.6	29.6	28.6
(4) Share Work Long Hours	26.0	32.9	29.2	26.4
(5) Share Long Hours - Fixed Age Comp.	26.0	32.9	29.2	25.9
(6) Share Long Hours - Fixed Share LH Young Workers	26.0	28.7	28.3	28.0

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers. Line (1) shows the share of 25-64 years old (young) workers among full-time employees in selected years. Lines (2) and (3) show, respectively, the share of long-hours employees among 25-44 year-old workers and among 45-64 year-old workers. Line (4) shows the corresponding share of employees usually working more than 48 hours per week. Line (5) contains the counterfactual shares of long hours employees if the share of young workers remained at its 1983-87 level (fixed age composition). Line (6) shows the counterfactual shares of long hours employees with constant age composition and long-hours incidence among young workers at its 1983-87 level. CPS weights applied, long hours defined as weekly hours above 48.

Table 3.2: Statistical Decomposition Ventennial Changes in Weekly Hours

	1980-1998				**1998-2016**			
Age Group	**25-34**	**35-44**	**45-54**	**55-64**	**25-34**	**35-44**	**45-54**	**55-64**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	College Graduate Salaried Male Workers							
$(\bar{h}_{t1} - \bar{h}_t)$	1.73	1.99	1.78	1.50	-2.09	-2.09	-1.02	-0.38
	Percentage *Extensive Margin* Contribution							
	86.80	76.20	76.87	71.29	99.73	95.92	88.87	84.89
	Percentage *Extensive Margin* Contribution - Alternative Counterfact.							
	79.97	71.65	70.45	63.33	101.85	99.08	93.26	88.79
	No College Salaried Male Workers							
$(\bar{h}_{t1} - \bar{h}_t)$	0.74	1.01	1.36	1.29	-1.65	-0.99	-0.58	0.11
	Percentage *Extensive Margin* Contribution							
	73.71	77.07	78.90	67.42	100.04	105.83	123.47	-59.24
	Percentage *Extensive Margin* Contribution - Alternative Counterfact.							
	71.03	73.49	74.15	57.18	98.92	103.84	119.60	-58.23

Notes: CPS Outgoing Rotation Groups. 25-64 years old male full-time salaried employees. Workers are divided in subgroups according to whether they hold a college degree or not. The table shows the overall change in average work hours observed over twenty-year intervals, $(\bar{h}_{t1} - \bar{h}_t)$ within each age-education group, and the share of the overall change in work-hours that can be explained by extensive-margins changes in the age-education-specific change in the share of salaried employees usually working more than 48 hours per week.

Table 3.3: Distribution of Salaried Workers across Occupation Classes

	1984	1994	2004	2014
	Shares of Workers by Occupation Class			
(a)	All Workers			
Professionals	40.23	42.92	44.01	47.03
White Collar	33.76	32.36	31.01	28.23
Blue Collar	26.00	24.72	24.98	24.74
(b)	Workers with College Degree			
Professionals	57.26	59.70	60.76	62.47
White Collar	36.90	34.50	32.47	29.61
Blue Collar	5.84	5.79	6.78	7.92
(c)	Workers without College Degree			
Professionals	26.25	27.04	26.23	27.39
White Collar	31.19	30.33	29.47	26.48
Blue Collar	42.57	42.63	44.30	46.13

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers. Balanced panel of 3-digit occupations constructed using Dorn (2009) classification, that I extend to cover the 2010 Census Occupations Classification. Professionals include executive, managerial, management related and professional specialty occupations. White collar include teachers, nurses, pharmacists, social workers, administrative assistants, technicians and sales workers. Blue collar include all remaining occupations. I define the three occupation classes following Eckstein & Nagypál (2004).

Table 3.4: Share of Long Workweek Salaried Employees Within Occupations

	1984	1994	2004	2014
	Workers with College Degree			
Professionals	27.00	37.15	35.45	30.47
White Collar	28.84	33.37	30.05	26.06
Blue Collar	23.31	29.62	26.96	24.93
	Workers without College Degree			
Professionals	24.29	34.21	31.65	29.28
White Collar	23.90	31.70	26.80	26.24
Blue Collar	21.02	27.47	22.36	23.23

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers. Long workweek employees usually work more than 48 hours per week. Balanced panel of 3-digit occupations constructed using Dorn (2009) classification, that I extend to cover the 2010 Census Occupations Classification. Professionals include executive, managerial, management related and professional specialty occupations. White collar include teachers, nurses, pharmacists, social workers, administrative assistants, technicians and sales workers. Blue collar include all remaining occupations. I define the three occupation classes following Eckstein & Nagypál (2004).

Table 3.5: Shift-Share Decomposition - % Employees Working Long Hours

	Δ_t^o (p.p.)	Between 2-Digit Occ.	Within 2-Digit Occ.: Between 3-Digit Occ.	Within 2-Digit Occ.: Within 3-Digit Occ.	% Within 3-Digit Occ.
(a)			25-34 year-old employees		
(1) 1979-82 to 1995-98	3.1	-.45	-.28	3.83	123%
(2) 1995-98 to 2015-18	-8.62	-.01	-.27	-8.33	97%
(b)			35-44 year-old employees		
(1) 1979-82 to 1995-98	3.94	-.76	-.40	5.11	130%
(2) 1995-98 to 2015-18	-6.51	.35	.12	-6.99	107%
(c)			45-54 year-old employees		
(1) 1979-82 to 1995-98	6.02	.41	-.17	5.77	96%
(2) 1995-98 to 2015-18	-3.09	-.33	.29	-3.05	99%
(d)			55-64 year-old employees		
(1) 1979-82 to 1995-98	3.75	.37	.03	3.35	89%
(2) 1995-98 to 2015-18	.63	-.03	.34	.31	49%

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers. Using Dorn (2009) and Meyer & Osborne (2005) occupation classification and expanding it to include occupations defined according to the 2010 Census classification, I maintain a balanced panel of 3-digit occupations that can be observed in all selected years. I only keep occupations where at least 50 workers are employed in every selected year. Employees are defined to work long hours if they usually work more than 40 hours per week.

Table 3.6: 5-Year Wage Growth and Working Long Hours across Cohorts

	All	Salaried	Hourly Paid	Salaried		Not Hourly	
				Prom	No Prom	Prom	No Prom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\hat{\gamma}_1$	0.067**	0.145***	0.017	0.143***	0.225	0.133***	-0.230
	(0.028)	(0.043)	(0.038)	(0.045)	(0.568)	(0.040)	(0.612)
$\hat{\gamma}_2$	0.112	0.180*	0.061	0.252**	-5.157	0.221*	-4.976
	(0.070)	(0.097)	(0.099)	(0.106)	(3.581)	(0.122)	(3.158)
$\hat{\gamma}_3$	0.061	0.021	0.078	-0.017	3.191**	-0.040	3.827**
	(0.041)	(0.057)	(0.060)	(0.061)	(1.534)	(0.058)	(1.764)
$\hat{\gamma}_4$	0.031	0.051	0.004	0.053	0.195	0.039	-5.266**
	(0.054)	(0.080)	(0.070)	(0.092)	(0.572)	(0.082)	(2.059)
N	4242	1473	2769	1124	349	1437	431
R^2	0.03	0.03	0.02	0.03	0.03	0.03	0.04

Notes: Panel Study of Income Dynamics (PSID), 1979 to 2018. The sample includes 30 to 34 year-old full-time male workers who are mostly observed working as employees (i.e. not self employed). $\hat{\gamma}_1$ is the estimated coefficient of working long hours when 25-29 years old for the cohort of workers turning 25 by year 1985. $\hat{\gamma}_2$, $\hat{\gamma}_3$, and $\hat{\gamma}_4$ are the estimated coefficients attached to the same variable for the cohorts turning 25, respectively, between 1986 and 1995, between 1996 and 2005, and after 2005. Robust standard errors in parentheses.

Table 3.7: 10-Year Wage Growth and Working Long Hours across Cohorts

	All	Salaried	Hourly Paid	Salaried		Not Hourly	
				Prom	No Prom	Prom	No Prom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\hat{\gamma}_1$	0.058	0.326***	-0.074	0.309***	0.027	0.155**	-0.249
	(0.055)	(0.082)	(0.061)	(0.089)	(0.806)	(0.073)	(0.887)
$\hat{\gamma}_2$	0.072	0.314***	-0.110	0.354***	0.572	0.295***	-1.305
	(0.084)	(0.116)	(0.113)	(0.130)	(2.863)	(0.104)	(2.721)
$\hat{\gamma}_3$	0.001	-0.095	0.054	-0.096	-1.154	-0.181*	1.232
	(0.066)	(0.077)	(0.104)	(0.084)	(3.003)	(0.099)	(2.828)
$\hat{\gamma}_4$	0.068	-0.377	0.228*	-0.526*	-0.877	-0.155	-0.877
	(0.169)	(0.285)	(0.117)	(0.304)	(1.702)	(0.263)	(1.696)
N	2475	902	1573	712	190	904	231
R^2	0.03	0.07	0.02	0.07	0.05	0.08	0.07

Notes: Panel Study of Income Dynamics (PSID), 1979 to 2018. The sample includes 30 to 34 year-old full-time male workers who are mostly observed working as employees (i.e. not self employed). $\hat{\gamma}_1$ is the estimated coefficient of working long hours when 25-29 years old for the cohort of workers turning 25 by year 1985. $\hat{\gamma}_2$, $\hat{\gamma}_3$, and $\hat{\gamma}_4$ are the estimated coefficients attached to the same variable for the cohorts turning 25, respectively, between 1986 and 1995, between 1996 and 2005, and after 2005. Robust standard errors in parentheses.

Table 3.8: Dynamic Returns of Working Long Hours

	(1) All Employees 25-55 y.o		(2) Salaried 25-55 y.o		(3) Hourly Paid 25-55 y.o		(4) Salaried 25-44 y.o		(5) Hourly Paid 25-44 y.o	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
$\varphi^{1981-85}$	0.259	0.245	0.216	0.348	0.241	0.188	0.231	0.273	0.241	0.165
	(0.018)	(0.035)	(0.022)	(0.044)	(0.026)	(0.050)	(0.026)	(0.049)	(0.030)	(0.053)
$\varphi^{1986-90}$	0.261	0.243	0.224	0.353	0.237	0.180	0.241	0.278	0.240	0.158
	(0.018)	(0.035)	(0.022)	(0.044)	(0.026)	(0.050)	(0.026)	(0.049)	(0.030)	(0.053)
$\varphi^{1991-95}$	0.278	0.251	0.237	0.362	0.254	0.186	0.253	0.285	0.262	0.167
	(0.018)	(0.035)	(0.022)	(0.044)	(0.026)	(0.051)	(0.026)	(0.049)	(0.031)	(0.053)
$\varphi^{1996-2000}$	0.287	0.262	0.248	0.374	0.261	0.196	0.267	0.301	0.272	0.181
	(0.019)	(0.035)	(0.023)	(0.044)	(0.027)	(0.051)	(0.026)	(0.049)	(0.031)	(0.053)
$\varphi^{2001-05}$	0.248	0.230	0.208	0.334	0.223	0.167	0.208	0.250	0.245	0.168
	(0.019)	(0.035)	(0.023)	(0.044)	(0.027)	(0.051)	(0.027)	(0.049)	(0.033)	(0.053)
$\varphi^{2006-10}$	0.242	0.213	0.217	0.332	0.205	0.138	0.199	0.228	0.223	0.135
	(0.020)	(0.036)	(0.024)	(0.044)	(0.029)	(0.051)	(0.029)	(0.050)	(0.035)	(0.055)
$\varphi^{2011-15}$	0.233	0.196	0.211	0.325	0.191	0.115	0.191	0.224	0.213	0.111
	(0.022)	(0.036)	(0.026)	(0.045)	(0.031)	(0.052)	(0.032)	(0.050)	(0.039)	(0.056)
N	50795	50795	20181	20181	30614	30614	14648	14648	23266	23266
R^2	0.45	0.05	0.54	0.14	0.34	0.02	0.53	0.13	0.32	0.03
adj. R^2	0.45	0.05	0.54	0.14	0.34	0.02	0.53	0.13	0.32	0.03

Notes: Control variables include a college-graduate dummy, a quadratic function of age and the full set of interactions between these variables and between each variable and time. The regressions do not control for current log-hours.

Table 3.9: The Relation between Wage Dispersion and Work Hours across Occupations

	1983-86	1995-98	2015-18
Std.Dev. of (log) Hourly Pay Residuals	0.244***	0.248***	0.103*
	(0.0614)	(0.0492)	(0.0616)
Real (log) Hourly Pay	-0.0247	0.0561***	0.0592***
	(0.0166)	(0.0160)	(0.0151)
Observations	148	148	148
R^2	0.522	0.632	0.446

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers. Using Dorn (2009) occupation classification and expanding it to include occupations defined according to the 2010 Census classification, I maintain a balanced panel of 3-digit occupations that can be observed in all selected years. I only keep occupations where at least 50 salaried workers are employed in every selected year. The average (log) real pay is computed for all salaried workers in an occupation. Hourly pay residuals are estimated from a mincerian regression of (log) wage on quadratic functions of age and of (log) work hours, an interaction of the age polynomial with a dummy for college graduates, and dummies for 3-digit occupations. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: Kuhn-Lozano Regression for 1984 to 1996

	(1) Wage Std.Dev	(2) Earnings Std.Dev	(3) Res. Earnings Std.Dev	(4) Res. Earnings p90-p10
Change Pay Dispersion	-0.020	0.030	-0.024	-0.055*
	(0.100)	(0.096)	(0.098)	(0.029)
R^2	0.000	0.001	0.000	0.024
N	146	146	146	146

Notes: CPS - ORG 25-64 year-old male full-time salaried workers. The table reports the results of a cross-occupation regression of changes in overtime work on changes in within-occupation residual wage dispersion. The changes are calculated between 1983-86 and 1995-98. The interval represents the time span when the surge in overtime work occurred. The table shows the coefficient of the within-occupation change in residual wage dispersion in different specifications using different definitions of wage inequality.

Table 3.11: Kuhn-Lozano Regression for 1996 to 2008

	(1) Wage Std.Dev	(2) Earnings Std.Dev	(3) Res. Earnings Std.Dev	(4) Res. Earnings p90-p10
Change Pay Dispersion	0.316***	0.261**	0.227**	0.148***
	(0.107)	(0.107)	(0.113)	(0.037)
Dummy for 2002	Y	Y	Y	Y
R^2	0.057	0.040	0.027	0.099
N	146	146	146	146

Notes: CPS - ORG 25-64 year-old male full-time salaried workers. The table reports the results of a cross-occupation regression of changes in overtime work on changes in within-occupation residual wage dispersion. The changes are calculated between 1995-98 and 2006-08. The models include a dummy for synthetic year 2002. The interval represents the time span when the decline in overtime work occurred. The table shows the coefficient of the within-occupation change in residual wage dispersion in different specifications using different definitions of wage inequality.

Table 3.12: Variance of Residual Wages among Newly Hired Workers

	1980s	1990s	2000s	2010s
All Workers	0.34	0.43	0.39	0.46
All Full-Time Workers	0.31	0.37	0.38	0.45
All Full-Time Employees	0.31	0.37	0.38	0.44

Notes: PSID Data. 25-64 years old male workers paid by the hour or on a salary basis. Wage dispersion is computed from residuals of decade-specific regressions of (log) hourly wages on a quadratic in age, a dummy for college graduates and an interaction of the college-dummy with the age polynomial. "All workers" are all self-employed and employees workers with non-missing wages in previous year, real wages between 1 and 100 $ and with exactly one job in previous year. This selection closely corresponds to Michelacci & Pijoan-Mas (2011) selection. “Full-Time Employees” drop self employed workers, and employees who work below 30 or above 98 hours per week. This selection closely corresponds to the sample I used in previous analyses.

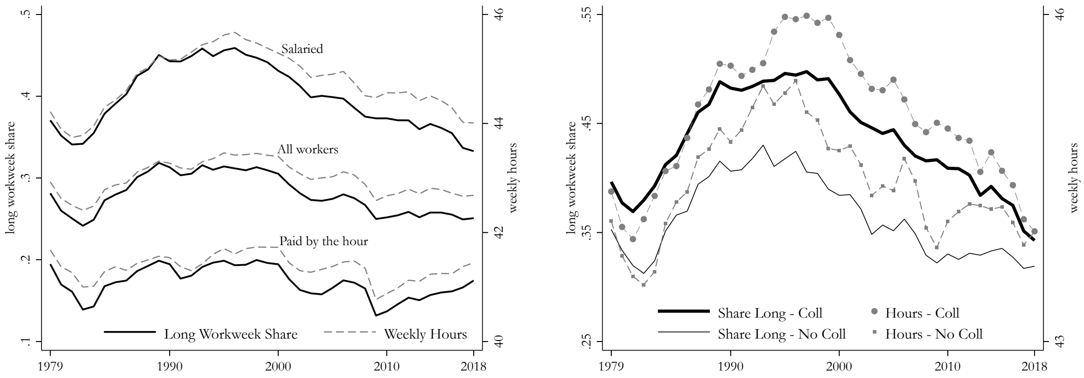
Table 3.13: Autocorrelation and Initial Residual Variance - Estimation Results

	HSV (2010)	My Estimation	
		College Grads	Salaried Employees
$\hat{\rho}$	0.973	0.968	0.957
90% CI		[0.959; 0.977]	[0.948; 0.966]
$\hat{\lambda}^{\eta}$	0.124	0.188	0.177
90% CI		[0.182; 0.193]	[0.171; 0.182]

Notes: PSID Data. Details on the sample selection and estimation are reported in the notes to figures 3.16 and 3.17. The first column in the table reports the values of the parameters estimated by Heathcote, Storesletten & Violante (2010). The second and third columns report the estimated parameter values I find for, respectively, college graduate workers, and workers paid on a salary basis (i.e. not paid by the hour).

3.7 Figures

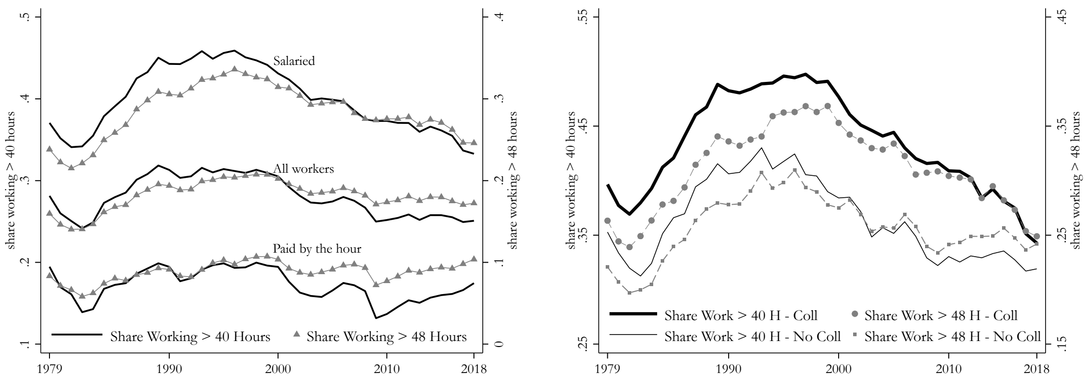
Figure 3.1: Share Working More than 40 Weekly Hours and Mean Weekly Hours



(a) All Workers (b) Salaried by Education

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers. I define CPS workers to be "salaried" if they are not paid by the hour. CPS weights applied.

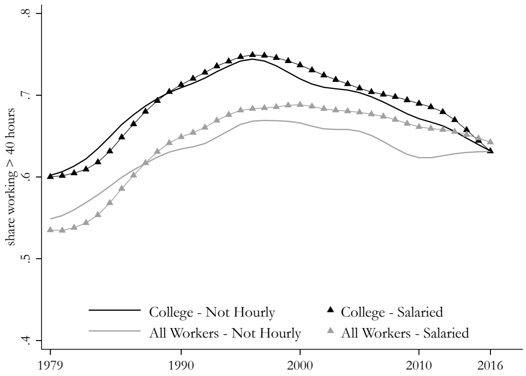
Figure 3.2: Share Working More than 40 Hours and Share Working More than 48 Hours



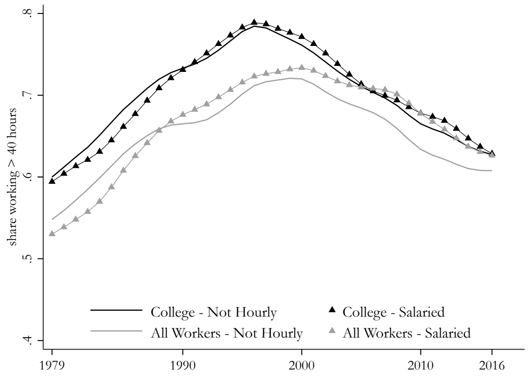
(a) All Workers (b) Salaried by Education

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers. I define CPS workers to be "salaried" if they are not paid by the hour.

Figure 3.3: Share Working More than 40 Hours - PSID



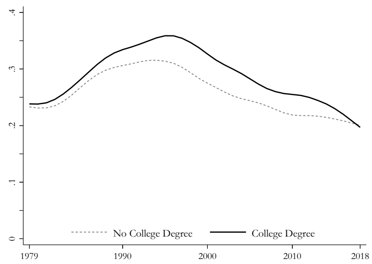
(a) 25-64 years old



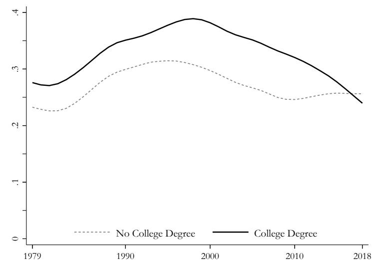
(b) 25-44 years old

Notes: The share of long hours employees is interpolated for all even years between 1998 and 2016, which are missing in the PSID. The figures show the Hodrick-Prescott smoothed series, with smoothing parameter 6.25.

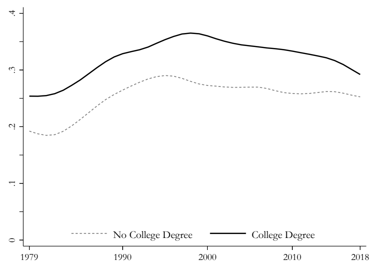
Figure 3.4: Salaried Workers by Age Group - Share Working > 48 hours ORG



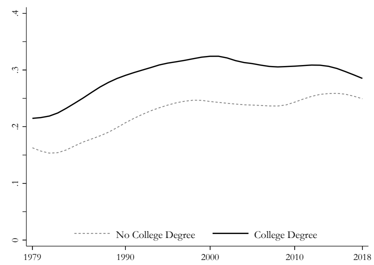
(a) 25-34 y.o.



(b) 35-44 y.o.



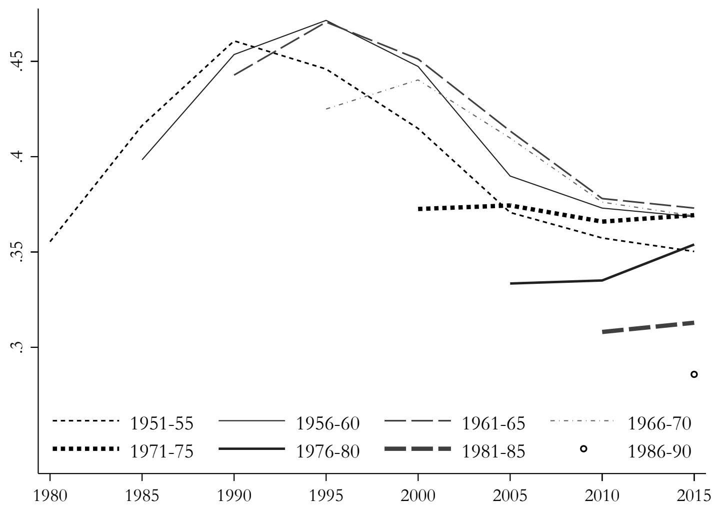
(c) 45-54 y.o.



(d) 55-64 y.o.

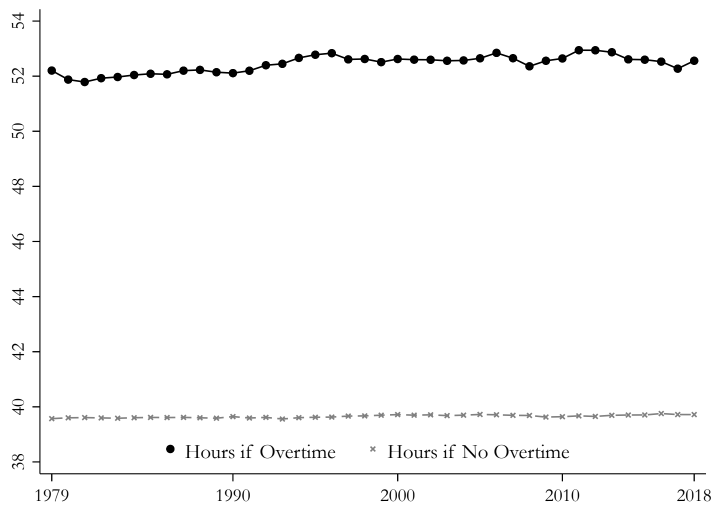
Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time male workers.

Figure 3.5: Overtime Work Over the Lifecycle by Cohort of Birth - ORG



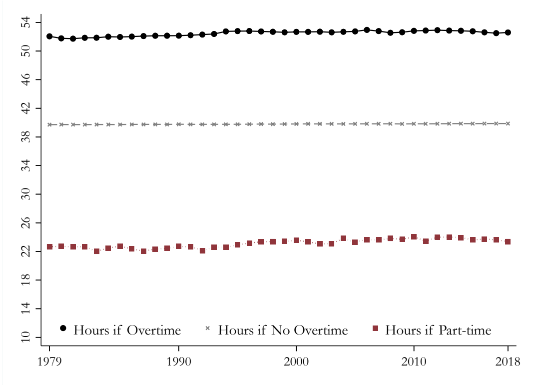
Notes: CPS-ORG. 25-64 year-old salaried employees working full-time with non-missing observations on hours and earnings. Cohorts are defined by year of birth and are reported in the legend. All cohorts can be observed when 25-29 year-old. The eldest cohort, born between 1951 and 1955 can be observed until 61-64 year-old. The likelihood of working long-hours is computed using sampling weights.

Figure 3.6: Work Hours - Full Time Salaried Employees by Overtime Status ORG

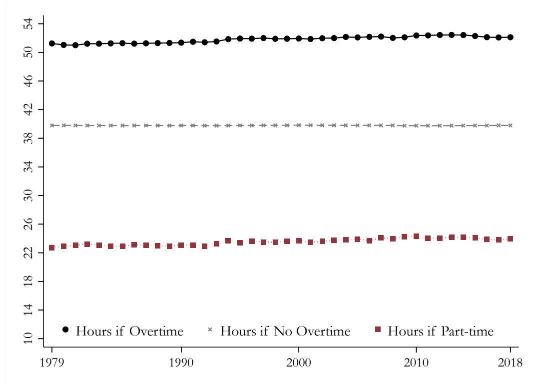


Notes: CPS-ORG. 25-64 year-old salaried employees working full-time with non-missing observations on hours and earnings. Employees are defined to work "overtime" is they report to usually work more than 40 hours per week; they are defined to work "no overtime" if they report to usually work between 30 and 40 hours per week.

Figure 3.7: Work Hours - Overtime, Full-Time, Part-Time Employees



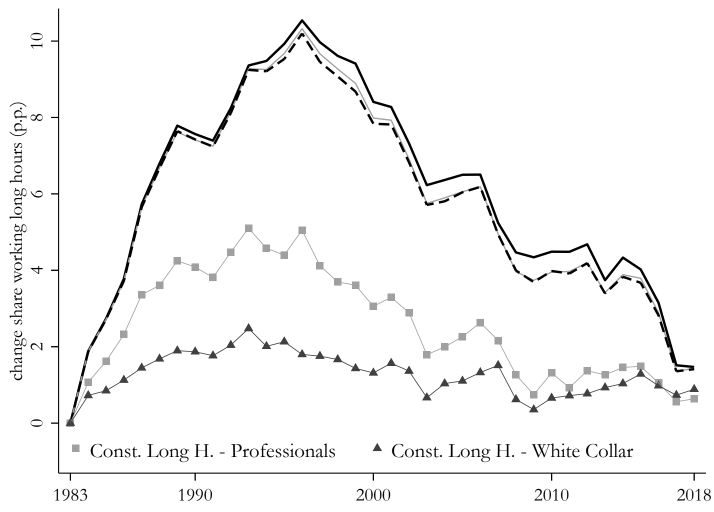
(a) Salaried



(b) All Workers

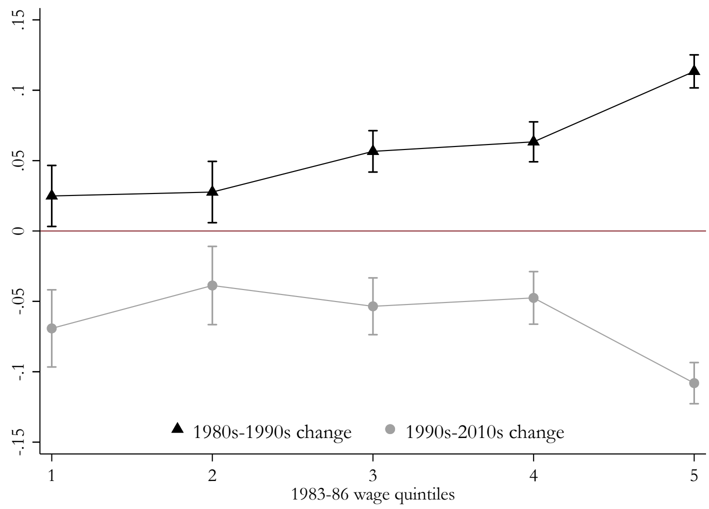
Notes: CPS-ORG. 25-64 year-old salaried employees with non-missing observations on hours and earnings. Employees are defined to work "overtime" is they report to usually work more than 40 hours per week; they are defined to work "no overtime" if they report to usually work between 30 and 40 hours per week; they are defined to work "part-time" if they usually work more than 5 hours and less than 30 hours per week.

Figure 3.8: The Contribution of Occupation Groups to the Trends in Long Workweeks



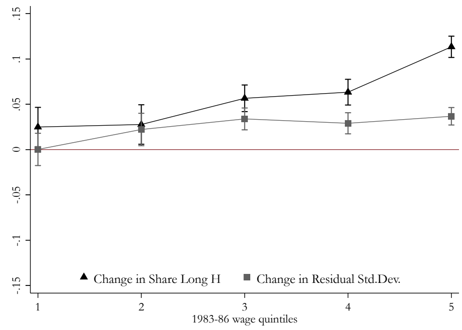
Notes: CPS-Outgoing Rotation Groups. 25-64 years old male full-time salaried employees. A long workweek is a workweek requiring more than 48 work-hours.

Figure 3.9: Changes in the Share of Long-Hours Employees by Quintiles of the 1980s Occupation Wage

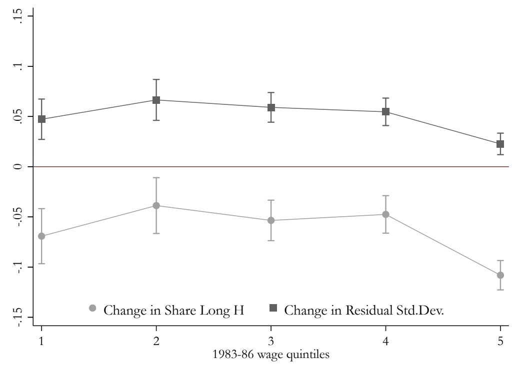


Notes: CPS-Outgoing Rotation Groups. 25-64 years old male full-time salaried employees. The sample includes a balanced panel of 3-digit occupations with at least 50 salaried employees in 1983-86, 1995-98 and 2015-18. The final sample includes 148 3-digit occupations. I limit my sample to employees working between 40 and 65 hours per week. This choice does not affect the results. Occupations are ranked into quintiles according to the mean occupation specific (log) real wage in 1983-86. The latter is computed for all salaried and hourly paid workers employed in the occupation. The construction of quintiles uses weights for each occupation, where weights are the occupation-specific employment share in 1983-86 among all workers. I run regressions of the change in the share of long-hours salaried employees on quintiles dummies separately for the time period 1983-86 to 1995-98 and 1995-98 to 2015-18. In each regressions, I use weights equal to the mean number of observations in each occupation between the two periods over which the change in the share of long-hours workers is computed. Workers are defined to work long hours if they usually work more than 48 hours per week.

Figure 3.10: 1983-86 to 1995-98 Changes in the Share of Long-Hours Employees and in Wage Dispersion by Quintiles of the 1980s Occupation Wage



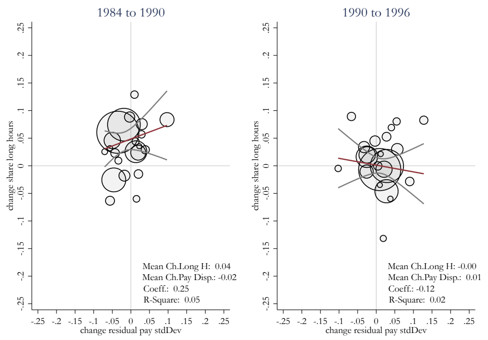
(a) Changes between 1983-86 and 1995-98



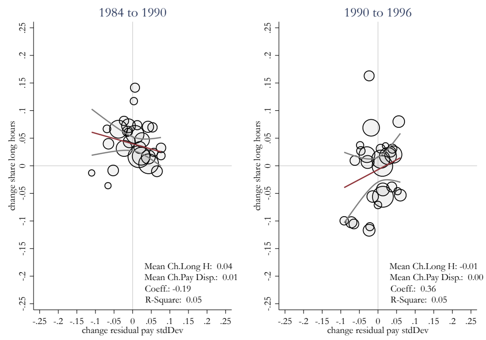
(b) Changes between 1995-98 and 2015-18

Notes: CPS-Outgoing Rotation Groups. 25-64 years old male full-time salaried employees. The sample includes a balanced panel of 3-digit occupations with at least 50 salaried employees in 1983-86, 1995-98 and 2015-18. The final sample includes 148 3-digit occupations. I limit my sample to employees working between 40 and 65 hours per week. This choice does not affect the results. Occupations are ranked into quintiles according to the mean occupation specific (log) real wage in 1983-86. The latter is computed for all salaried and hourly paid workers employed in the occupation. The construction of quintiles uses weights for each occupation, where weights are the occupation-specific employment share in 1983-86 among all workers. I run regressions of the change in the share of long-hours salaried employees on quintiles dummies separately for the time period 1983-86 to 1995-98 and 1995-98 to 2015-18. In each regressions, I use weights equal to the mean number of observations in each occupation between the two periods over which the change in the share of long-hours workers is computed. Workers are defined to work long hours if they usually work more than 48 hours per week.

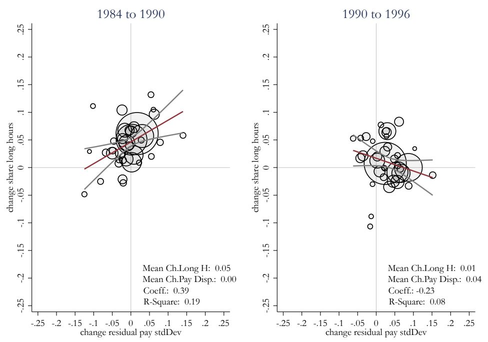
Figure 3.11: 1984 to 1990 and 1990 to 1996 Cross-Occupation Correlation between Increase in Overtime Work and Increase in Wage Dispersion.



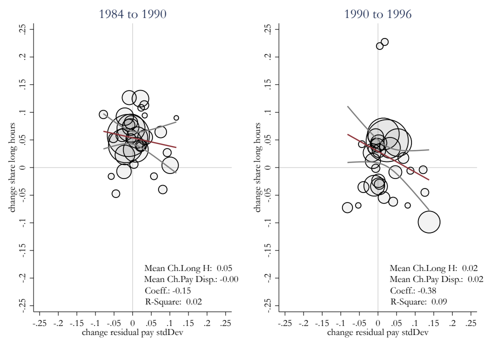
(a) Quintile 1



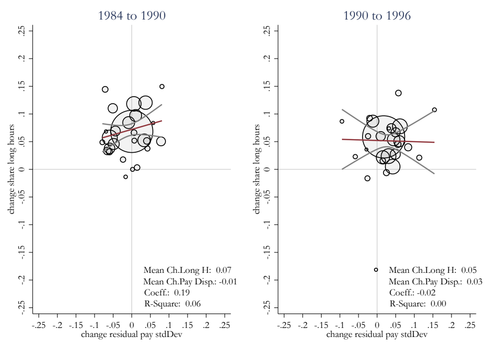
(b) Quintile 2



(c) Quintile 3



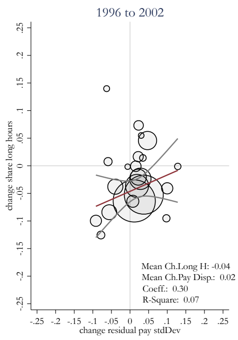
(d) Quintile 4



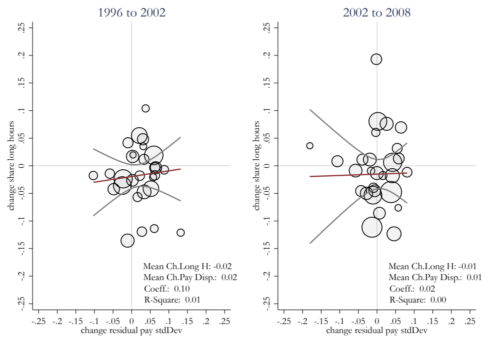
(e) Quintile 5

Notes: CPS-Outgoing Rotation Groups. 25-64 years old male full-time salaried employees.

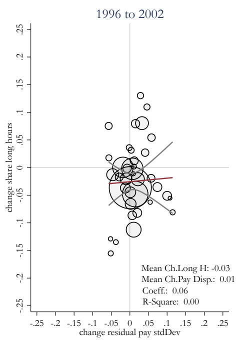
Figure 3.12: 1996 to 2002 and 2002 to 2008 Cross-Occupation Correlation between Increase in Overtime Work and Increase in Wage Dispersion.



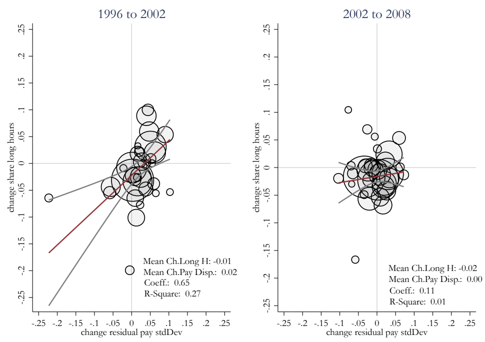
(a) Quintile 1



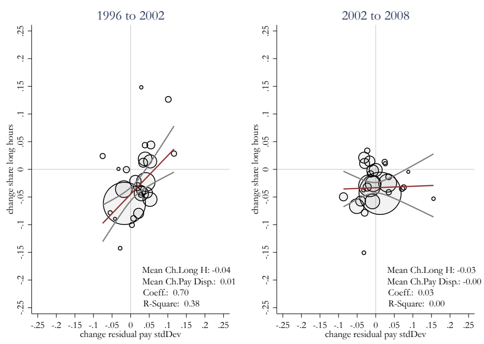
(b) Quintile 2



(c) Quintile 3



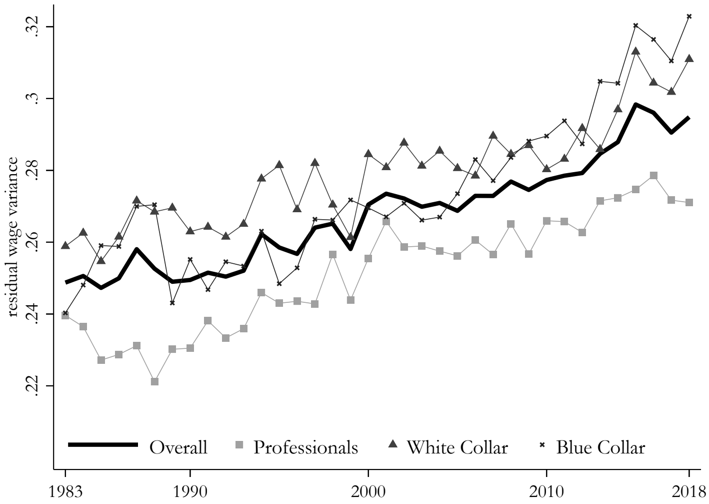
(d) Quintile 4



(e) Quintile 5

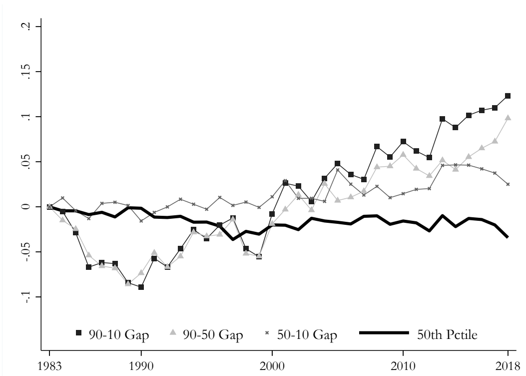
Notes: CPS-Outgoing Rotation Groups. 25-64 years old male full-time salaried employees.

Figure 3.13: Trends in Residual Wage Variance in CPS - Salaried Workers

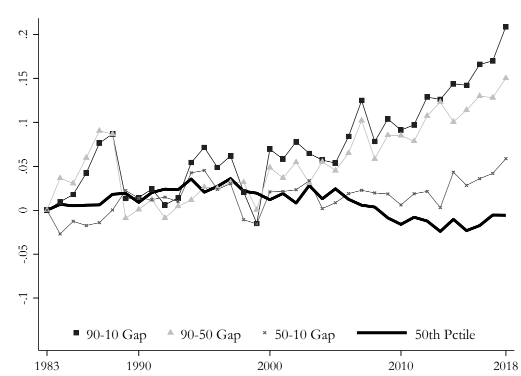


Notes: CPS - ORG 25-64 year-old male full-time salaried workers. Variance is computed from the residuals of year-specific regressions of (log) real wages on a quadratic in age, a dummy for college graduates, interactions between the college dummy and the age polynomial, and controls for 3-digit occupations. CPS weights applied.

Figure 3.14: Trends in Residual Percentiles Gaps - Salaried Workers



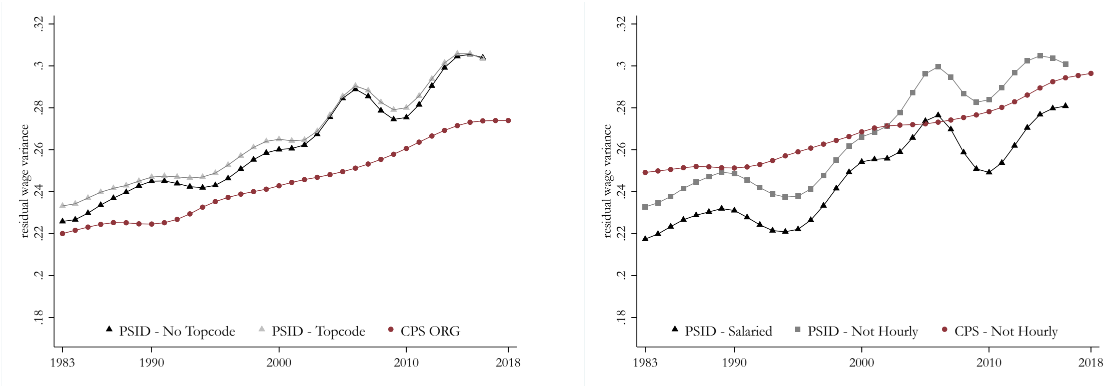
(a) Professionals



(b) White Collar

Notes: CPS - ORG 25-64 year-old male full-time salaried workers. Percentiles gaps are computed from the residuals of year-specific regressions of (log) real wages on a quadratic in age, a dummy for college graduates, interactions between the college dummy and the age polynomial, and controls for 3-digit occupations. CPS weights applied.

Figure 3.15: Trends in Residual Wage Variance in CPS and PSID

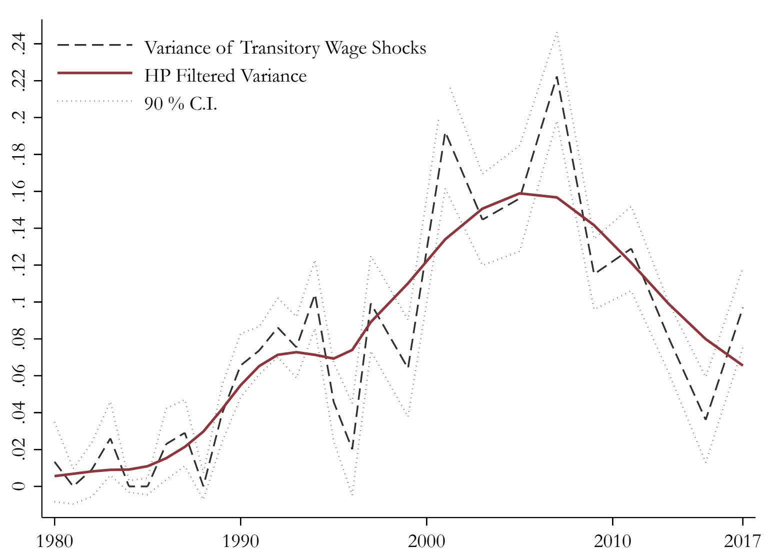


(a) All Workers

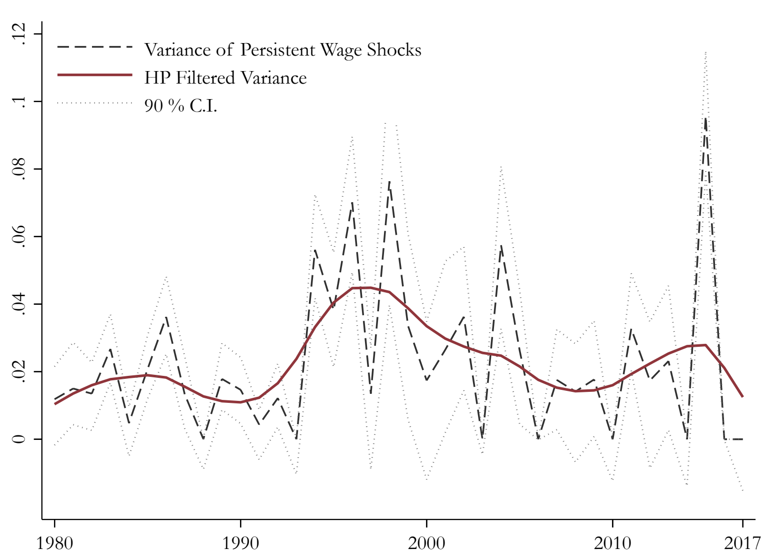
(b) Not Paid by the Hour

Notes All series are HP-filtered with smoothing parameter 6.25. PSID sample only includes workers paid on a salary basis and workers paid on a hourly basis.

Figure 3.16: Persistent and Transitory Wage Shock Variances - College Graduates



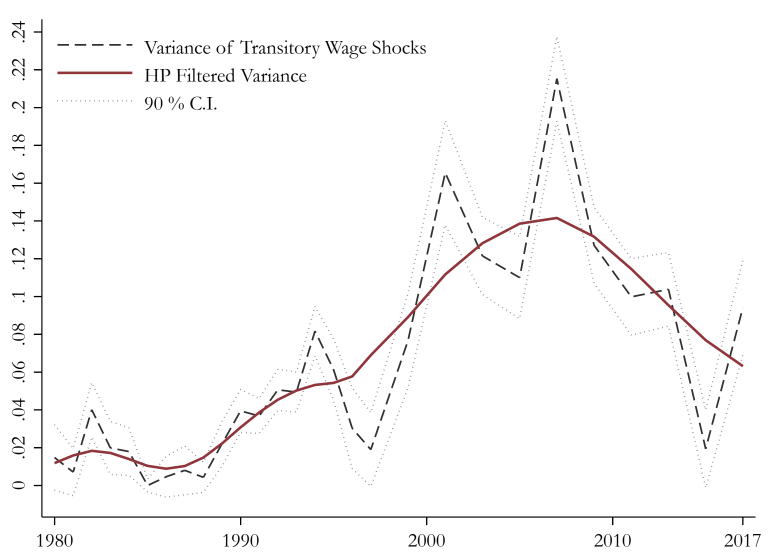
(a) Transitory Wage Shocks



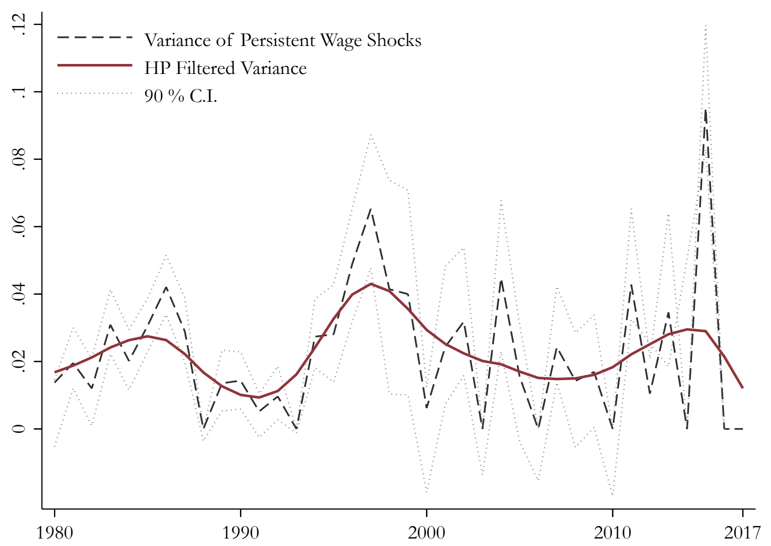
(b) Persistent Wage Shocks

Notes PSID. The estimation sample includes 25-64 year-old college graduate male household heads who work full-time and who report to work as employees (i.e. not self-employed) most of the times in which they are observed in PSID data. The variance of the transitory component of individual wage residuals is computed as follows. First, I run regressions of individual (log) hourly wages on a cubic function of workers age, and I isolate the wage residuals. I then use empirical variances and auto-covariances of individual wage residuals over workers' age and estimate λ_t^ν through minimum distance estimator with waiting matrix equal to the identity matrix as in Heathcote, Storesletten & Violante (2010). The maroon line shows the HP-filtered time series of the transitory wage variance, computed with smoothing parameter equal to 6.25 as suggested by Ravn & Uhlig (2002) when using annual data. The figure also reports the 90% confidence interval for the parameter estimate, where the confidence interval is constructed using bootstrapped standard errors with 500 replications.

Figure 3.17: Persistent and Transitory Wage Shock Variances - Not Paid by Hour



(a) Transitory Wage Shocks



(b) Persistent Wage Shocks

Notes PSID. The estimation sample includes 25-64 year-old male household heads who work full-time and who (1) report to work as employees (i.e. not self-employed) most of the times in which they are observed in PSID data and (2) report not to be paid by the hour most of the times in which they are observed in PSID data. The variance of the transitory component of individual wage residuals is computed as follows. First, I run regressions of individual (log) hourly wages on a cubic function of workers age, a dummy controlling for whether a worker has a college degree, and a full set of interactions between the college dummy and the age polynomial. I hence retain individual wage residuals. I then use empirical variances and auto-covariances of individual wage residuals over workers' age and estimate λ_t^{ω} through minimum distance estimator with waiting matrix equal to the identity matrix as in Heathcote, Storesletten & Violante (2010). The maroon line shows the HP-filtered time series of the transitory wage variance, computed with smoothing parameter equal to 6.25 as suggested by Ravn & Uhlig (2002) when using annual data. The figure also reports the 90% confidence interval for the parameter estimate, where the confidence interval is constructed using bootstrapped standard errors with 500 replications.

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Appendix A

Appendix to Chapter 1

A.1 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.

A.1.1 Information of Interest

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

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

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

Labor Market Information is divided between:

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

b. Information pertaining to an year;

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

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

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

Regarding point *c.*, detailed information about job and employer characteristics is available. I retain information about all available jobs. This information is collected once for each round and does not change within a year. For each job, the NLSY provides a person-specific unique identifier that allows to match the characteristics of each job to all weeks in which the workers was employed in a given job. The identifier is employer specific, implying that a change of job consists of a change of employer. Since the firm identifier is only unique within individuals, it is not possible to observe whether two or more individuals are employed by the same firm. In the next section I will detail the procedure I followed to merge job-to-week specific information.

The job-specific information contained in the NLSY includes the day, month and year in which an employment relationship starts and ends. For ongoing jobs, in each interview the start date coincides with the end date as of the preceding interview, and the end date corresponds with the interview date. The survey also reports the hourly wage as of the interview date or at the time the employment relationship ended, the hourly compensation, the usual number of weekly hours worked, the actual number of weeks worked between two successive survey interviews, 4 digit occupation an industry codes, whether the worker is in an internship, whether he/she is self employed or in an employee job, whether the worker is covered by a union-bargained contract.

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

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

A.1.2 Merging Weekly and Job-Year 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.

When possible, I also impute job-specific information when the latter is missing due to errors in reporting. 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.

I impute the wages of employed workers with 0$ wages. 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 1.2.

A.2 Descriptive Statistics: Alternative Samples

Table A.1: 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 A.2: 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 A.3: 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 A.4: 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 A.5: 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 A.6: 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 A.7: 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 A.8: 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 A.9: 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 A.10: 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

A.3 Composition Adjusted Wages

A.3.1 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

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

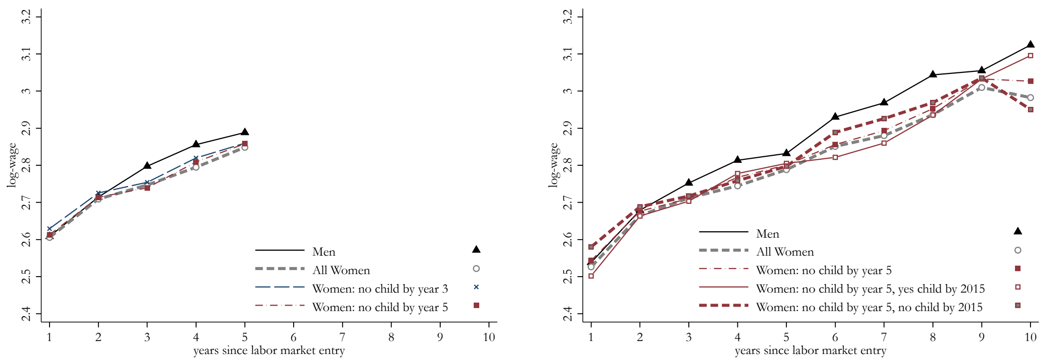
Where the subscript t indicates that a separate regression is estimated for every year of experience, so that coefficients of all variables are allowed to vary across years in the labor market.

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.[1] 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.

[1] 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.

A.3.2 Composition Adjusted Wages: Robustness Checks

Figure A.1: 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)).

A.4 Returns to Experience: Estimates

Table A.11: Light and Ureta (1995) Experience Models Estimated Coefficients

	WH M b/se	WH F b/se	AE M b/se	AE F b/se	PE M b/se	PE F b/se
WH = % Year worked (t-1)	0.0961**	0.1478***				
	(0.0409)	(0.0319)				
WH = % Year worked (t-2)	0.1012***	0.0558*				
	(0.0371)	(0.0291)				
WH = % Year worked (t-3)	0.0759**	0.0950***				
	(0.0367)	(0.0287)				
WH = % Year worked (t-4)	0.0571	0.0435				
	(0.0370)	(0.0289)				
WH = % Year worked (t-5)	0.1227***	0.0678**				
	(0.0380)	(0.0300)				
WH = % Year worked (t-6)	0.0548	0.0791**				
	(0.0399)	(0.0318)				
WH = % Year worked (t-7)	0.1161***	0.0735**				
	(0.0424)	(0.0343)				
WH = % Year worked (t-8)	0.0746	0.0676*				
	(0.0455)	(0.0384)				
WH = % Year worked (t-9)	0.0589	0.0543				
	(0.0531)	(0.0449)				
Years 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 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 = % 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 A.12: 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.

A.5 Wage Gap Decomposition: Results and Robustness

Table A.13: 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 1.1. 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 A.2: 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.

A.6 Returns to Job Changes

Table A.14: Returns to Job Change - All Coefficients

	Baseline + Contr		Baseline + Y Dummies		Baseline + Y Trend		Baseline + more Contr	
	M	F	M	F	M	F	M	F
	(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 Exp=AE (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)^2	-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 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**[Ch(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)^2***I**[Ch(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 Deg 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)
In School 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) Week Hours 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)
Tenure 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^2	-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 contract 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) Employees at j 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)
Parent Benefits 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)
Flex Schedule 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 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)
Unemp Rate 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)
Med Insur t-2							0.0498	-0.1005
							(0.0590)	(0.1050)
Life Insur t-2							-0.0265	-0.0215
							(0.0446)	(0.0553)
Dental Care t-2							-0.0984	0.1678*
							(0.0834)	(0.0952)
Retir Plan t-2							0.0941*	0.0426
							(0.0480)	(0.0602)
Stock Own 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
Occ & Ind $t-2$	N	N	N	N	N	N	Y	Y

Notes: NLSY97. Sample as in Table 1.1.

Table A.15: Returns to Job Change - By Reason Driving Job Change

	Baseline + Contr		Baseline + Y Dummies		Baseline +Y Trend		Baseline + more Contr	
	M	F	M	F	M	F	M	F
	(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 Exp=AE(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)^2	-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[Ch(t-1)]*Job*Dest*(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)
*Shop(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)
*Family(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)
*Dislikes J(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)
*Other(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)
*Mobility(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**[Ch]*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)
*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)
*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)
*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)
*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)
*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)^2***I**[Ch]*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)
*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)
*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)
*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)
*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
Occ & Ind $t-2$	N	N	N	N	N	N	Y	Y

Notes: NLSY97. Sample as in Table 1.1.

A.7 Estimating the Average Elasticity of the Probability of Job Change following Kitazawa (2012)

Given the Conditional Logit Model

$$\begin{aligned} y^*_{ijt} &= z'_{ijt}\xi + \nu_i + u_{ijt} \\ &= \alpha + \beta w_{it} + \gamma \mathbf{I}\left[\text{Parental Benefits}_{ijt}\right] + \delta \mathbf{I}\left[\text{Flexible Schedule}_{ijt}\right] + x'_{ijt}\eta + \nu_i + u_{ijt} \end{aligned} \tag{A.1}$$

$$y_{ijt} = \mathbf{I}\left[j(t) \neq j(t+1)\right] = \mathbf{I}\left[y*_{ijt} \geq 0\right] \tag{A.2}$$

$$\Pr\left[y_{ijt} = 1 | z_{ijt}, \nu_i\right] = \frac{\exp\{z'_{ijt}\xi + \nu_i\}}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \tag{A.3}$$

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

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

Following Kitazawa (2012), let $N \to \infty$ and T constant. The model in (A.2) and (A.3) can be rewritten as

$$y_{ijt} = p_{ijt} + u_{ijt} \tag{A.4}$$

$$p_{ijt} = \Pr\left[y_{ijt} = 1 | z_{ijt}, \nu_i\right] \tag{A.5}$$

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

$$\begin{aligned} \eta^{Z^k}_{ijt} &= \frac{\partial p_{ijt}}{\partial Z^k_{ijt}} \frac{Z^k_{ijt}}{p_{ijt}} = \xi_k \frac{1}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \\ &= \xi_k \left(1 - p_{ijt}\right) \end{aligned} \tag{A.6}$$

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

$$\bar{\eta} = \hat{\xi}_k \left(1 - \bar{y}\right) \tag{A.7}$$

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

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

$$\begin{aligned}
\zeta^{Z^k}_{it} &= \frac{\partial p_{ijt}}{\partial Z^k_{ijt}} \frac{1}{p_{ijt}} \\
&= \xi_k \frac{1}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \\
&= \xi_k \left(1 - p_{ijt}\right)
\end{aligned} \tag{A.8}$$

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

$$\begin{aligned}
\frac{p^1_{ijt} - p^0_{ijt}}{p^0_{ijt}} &= \left(\exp\{\xi_k\} - 1\right) \frac{1}{1 + \exp\{z'_{ijt}\xi + \nu_i\}} \\
&\approx \xi_k \left(1 - p^1_{ijt}\right)
\end{aligned} \tag{A.9}$$

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 A.16: 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

Notes: NLSY97. Sample as in Table 1.1. 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.

Appendix B

Appendix to Chapter 2

B.1 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

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

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

$$\begin{aligned} F(w^*|.) &= P(\mu^w(X) + \rho'\mathbf{a} + \sigma_w \varepsilon_w \leq w^*) \\ &= P\left(\varepsilon_w \leq \frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right) \\ &= \Phi\left(\frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right) \end{aligned} \tag{B.2}$$

So that

$$f(w^*|.) = \frac{1}{\sigma_w}\phi\left(\frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right) \tag{B.3}$$

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,

$$P(a_k^*|.) = p^{a_k^*}(1-p)^{1-a_k^*} \tag{B.4}$$

Where

$$\begin{aligned} p &= P(\mu^{a_k}(X) + \varepsilon_{a_k} > 0) \\ &= P(\varepsilon_{a_k} > -\mu^{a_k}(X)) \\ &= 1 - \Phi(-\mu^{a_k}(X)) = \Phi(\mu^{a_k}(X)) \end{aligned} \tag{B.5}$$

So that, for each amenity a_k

$$\begin{aligned} P(a_k^*|.) &= \Phi(\mu^{a_k}(X))^{a_k^*}(1 - \Phi(\mu^{a_k}(X)))^{1-a_k^*} \\ &= \Phi\left(\mu^{a_k}(X)(-1)^{(1-a_k^*)}\right) \end{aligned} \tag{B.6}$$

Substituting (B.3) and (B.6) in (B.1)

$$f(w^*, \mathbf{a}^*|.) = \frac{1}{\sigma_w}\phi\left(\frac{w^* - \mu^w(X) - \rho'\mathbf{a}}{\sigma_w}\right)\prod_{k=1}^{K}\Phi\left(\mu^{a_k}(X)(-1)^{(1-a_k^*)}\right) \tag{B.7}$$

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

$$\bar{F}_u(u|.) = \sum_{\mathbf{a}^* \in \{0,1\}^K} \bar{F}(u|\mathbf{a}^*, .)P(\mathbf{a}^*|.) \tag{B.8}$$

Where

$$
\begin{aligned}
\bar{F}(u|\mathbf{a}^*, .) &= 1 - P(w^* + \delta'\mathbf{a}^* \leq u|.) \\
&= 1 - P(\mu^w(X) + \rho'\mathbf{a}^* + \sigma_w\varepsilon_w + \delta'\mathbf{a}^* \leq u) \\
&= 1 - P\left(\varepsilon_w \leq \frac{-(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right) \\
&= 1 - \Phi\left(-\frac{(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right) \\
&= \Phi\left(\frac{(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right) \qquad \text{(B.9)}
\end{aligned}
$$

Substituting (B.9) and (B.6) into (B.8)

$$
\bar{F}_u(u|.) = \sum_{\mathbf{a}^* \in \{0,1\}^K} \Phi\left(\frac{(\mu^w(X) + \rho'\mathbf{a}^* + \delta'\mathbf{a}^* - u)}{\sigma_w}\right) \prod_{k=1}^{K} \Phi\left(\mu^{a_k}(X)(-1)^{(1-a_k^*)}\right) \qquad \text{(B.10)}
$$

B.2 The Bonhomme & Jolivet Estimation

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 (2.11) can be rewritten as

$$l_{t+1}(\theta, \lambda, \delta) = l_{1,t+1}(\theta) \times l_{2,t+1}(\theta, \lambda, \delta) \times l_{3,t+1}(\theta, \lambda, \delta) \tag{B.11}$$

$$l_{1,t+1}(\theta) = f(w_{t+1}, a_{t+1}; \theta)^{uj_t} \tag{B.12}$$

$$l_{2,t+1}(\theta, \lambda, \delta) = [1 - \lambda_1 \bar{F}(w_t + \delta' \mathbf{a}_t; \theta) - \lambda_2 - q]^{s_t} [\lambda_1 \bar{F}(w_t + \delta' \mathbf{a}_t; \theta) + \lambda_2]^{jj_t} \tag{B.13}$$

$$l_{3,t+1}(\theta, \lambda, \delta) = \\ q^{ju_t} [1 - \lambda_0]^{uu_t} \lambda_0^{uj_t} \left[\frac{(\mathbf{1}\{w_{t+1} + \delta' \mathbf{a}_{t+1} > w_t + \delta' \mathbf{a}_t\} + \lambda_2) f(w_{t+1}, a_{t+1}; \theta)}{\lambda_1 \bar{F}(w_t + \delta' \mathbf{a}_t; \theta) + \lambda_2} \right]^{jj_t} \tag{B.14}$$

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

$$\hat{\theta} = \text{argmax}_\theta \log L_1 = \text{argmax}_\theta \sum_{i=1}^{N} \sum_{t=t_0}^{T} \log l_{1,t+1} \tag{B.15}$$

Second, taking $\hat{\theta}$, I guess an initial value $\tilde{\delta}$ and estimate

$$\hat{\lambda}^1 = \text{argmax}_\lambda \log L_2 + \log L_3 = \text{argmax}_\lambda \sum_{i=1}^{N} \sum_{t=t_0}^{T} \log l_{2,t+1}(\hat{\theta}, \lambda, \tilde{\delta}) + \log l_{3,t+1}(\hat{\theta}, \lambda, \tilde{\delta}) \tag{B.16}$$

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 $\hat{\delta}^1$

$$\hat{\delta}^1 = \text{argmax}_\delta \log L_2 = \text{argmax}_\delta \sum_{i=1}^{N} \sum_{t=t_0}^{T} \log l_{2,t+1}(\hat{\theta}, \hat{\lambda}^1, \delta) \tag{B.17}$$

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 $t \in (1, T)$.

B.3 Structural Parameter Estimates

Table B.1: 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 B.2: 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 B.3: 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 B.4: 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.

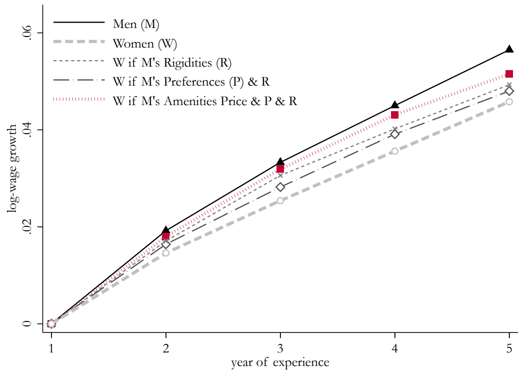
Table B.5: Estimated Childcare Parameters

	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]

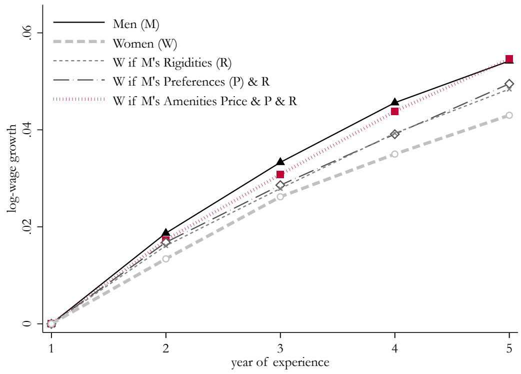
National Longitudinal Survey of Youth, 1997.

B.4 Counterfactual Wage Growth By Career

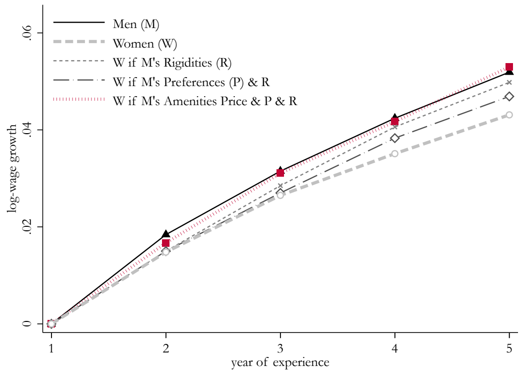
Figure B.1: Predicted Log-Wage Profiles - Administrative, Education, Health, and Social Services Sector



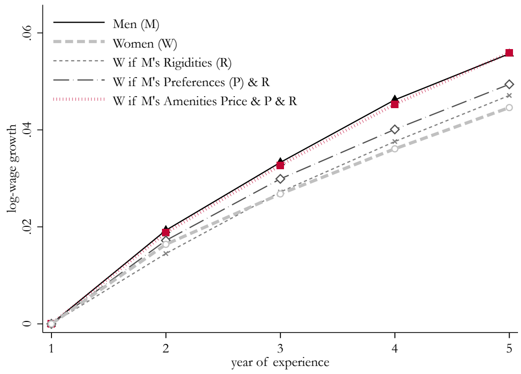
(a) Administratives



(c) Executives



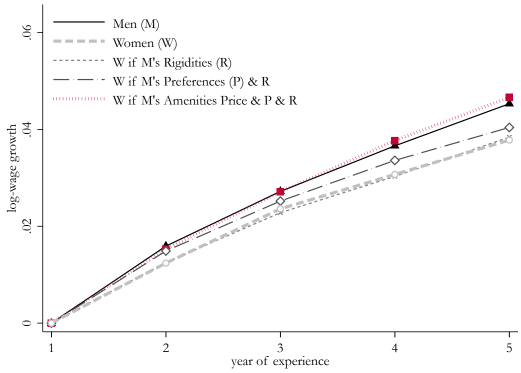
(d) Professionals



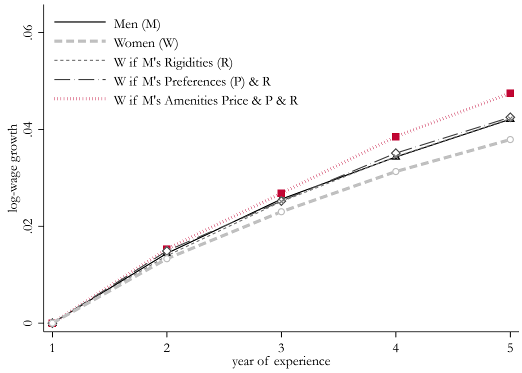
(b) Others

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

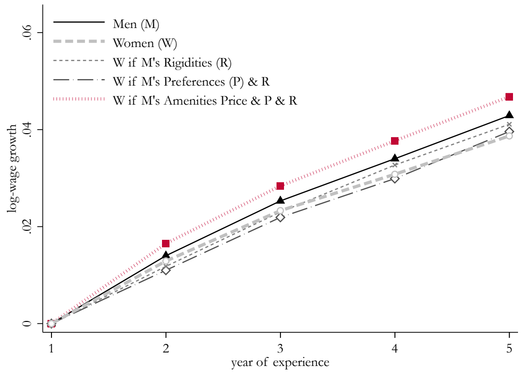
Figure B.2: Predicted Log-Wage Profiles - Finance, Information, Real Estate



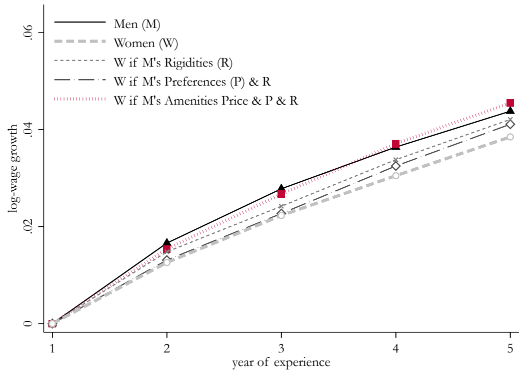
(a) Administratives



(b) Executives



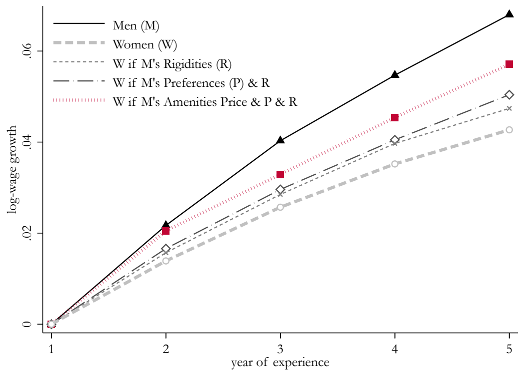
(c) Professionals



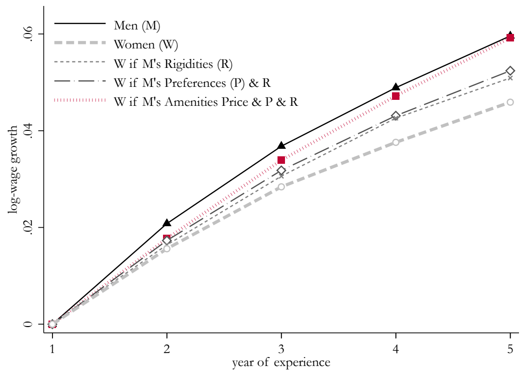
(d) Others

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

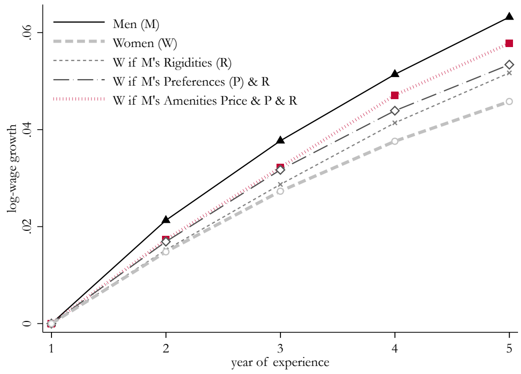
Figure B.3: Predicted Log-Wage Profiles - Trade Sector



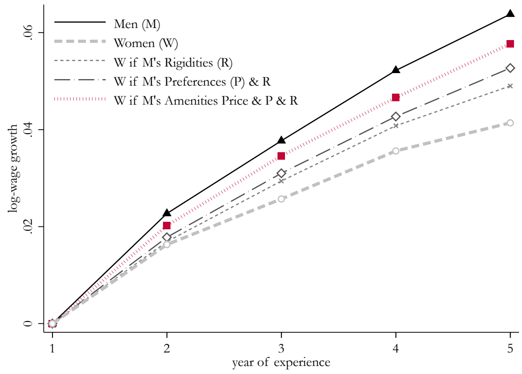
(a) Administratives



(c) Executives



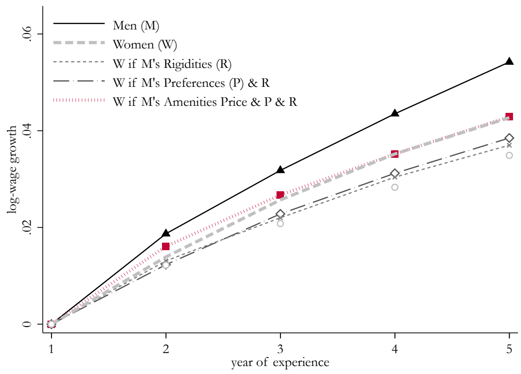
(d) Professionals



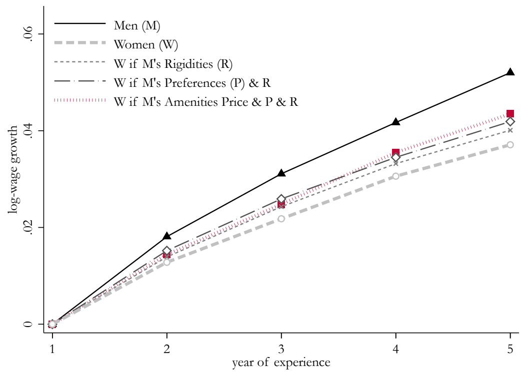
(b) Others

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

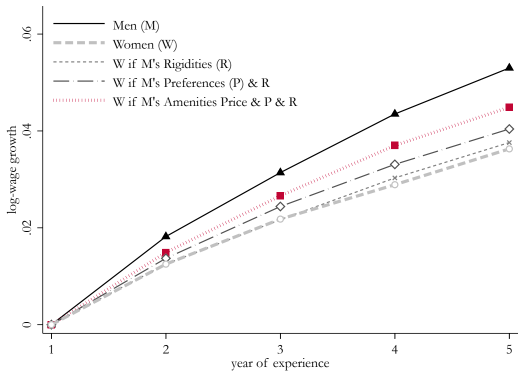
Figure B.4: Predicted Log-Wage Profiles - Other Sectors



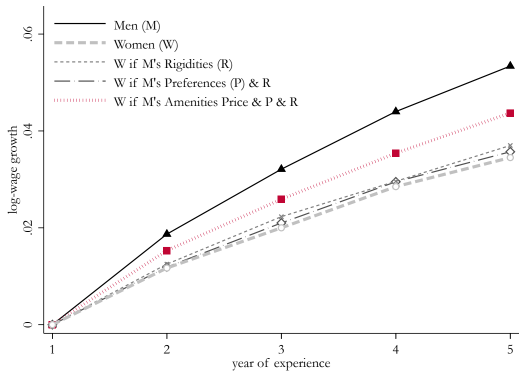
(a) Administratives



(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.

B.5 Expected Utility Decomposition

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

$$\begin{aligned}
E(u|g, b, \text{car}_{oc}, \text{car}_{in}) &= E(w + \delta'\mathbf{a}|g, b, \text{car}_{oc}, \text{car}_{in}) \\
&= \mu_0^g + \mu_1^g b + \sum_{oc=1}^{3} \varphi_{oc}^{g,w} \text{car}_{oc} + \sum_{in=1}^{3} \varphi_{in}^{g,w} \text{car}_{in} + \\
&+ \sum_{k=1}^{4} \rho_k^g \text{P}(a_k^{of} = 1|g, b, \text{car}_{oc}, \text{car}_{in}) + \\
&+ \sum_{k=1}^{4} \delta_k^g \text{P}(a_k^{of} = 1|g, b, \text{car}_{oc}, \text{car}_{in}) \\
&= \mu_0^g + \mu_1^g b + \sum_{oc=1}^{3} \varphi_{oc}^{g,w} \text{car}_{oc} + \sum_{in=1}^{3} \varphi_{ind}^{g,w} \text{car}_{in} + \\
&+ \sum_{k=1}^{4} \rho_k^g \Phi \left(\mu_0^{g,a_k} + \mu_1^{g,a_k} b + \sum_{oc=1}^{3} \varphi_{oc}^{g,a_k} \text{car}_{oc} + \sum_{in=1}^{3} \varphi_{in}^{g,a_k} \text{car}_{in} \right) \\
&+ \sum_{k=1}^{4} \delta_k^g \Phi \left(\mu_0^{g,a_k} + \mu_1^{g,a_k} b + \sum_{oc=1}^{3} \varphi_{oc}^{g,a_k} \text{car}_{oc} + \sum_{in=1}^{3} \varphi_{ind}^{g,a_k} \text{car}_{in} \right)
\end{aligned} \tag{B.18}$$

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

$$\begin{aligned}
\hat{E}(u|f, .) - \hat{E}(u|m, .) &= \left[(\hat{\mu}_0^f + \hat{\varphi}_j^{f,w} + \hat{\varphi}_\tau^{f,w}) - (\hat{\mu}_0^m + \hat{\varphi}_j^{m,w} + \hat{\varphi}_\tau^{m,w}) \right] + (\hat{\mu}_1^f - \hat{\mu}_1^m) b + \\
&+ \sum_{k=1}^{4} \hat{\rho}_k^f \left[\hat{\Phi}^f(.) - \hat{\Phi}^m(.) \right] + \sum_{k=1}^{4} \hat{\Phi}^m(.) \left(\hat{\rho}_k^f - \hat{\rho}_k^m \right) \\
&+ \sum_{k=1}^{4} \hat{\delta}_k^f \left[\hat{\Phi}^f(.) - \hat{\Phi}^m(.) \right] + \sum_{k=1}^{4} \hat{\Phi}^m(.) \left(\hat{\delta}_k^f - \hat{\delta}_k^m \right)
\end{aligned} \tag{B.19}$$

The left-hand side of the first line of equation (B.19) 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 B.6 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 B.6 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 B.6: Predicted Utility Gap Decomposition - Female-to-Male

	(a) Admin., Educ. Health, Social Serv.			**(b) Financial Services**		
	(1) Admin.	(2) Exec.	(3) Prof.	(1) Admin.	(2) Exec.	(3) Prof.
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: NLSY97. Contribution of different factors to the gap in surplus from employment relationships between male and female workers. Economic sectors are: Administrative, Education, Health and Social Services (panel (a)) and Financial Services (panel (b)). Occupations are: Administrative (1), Executive (2), Professional (3). *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.

Appendix C

Appendix to Chapter 3

C.1 Average Work-Hours and Share of Long-Hours Employees

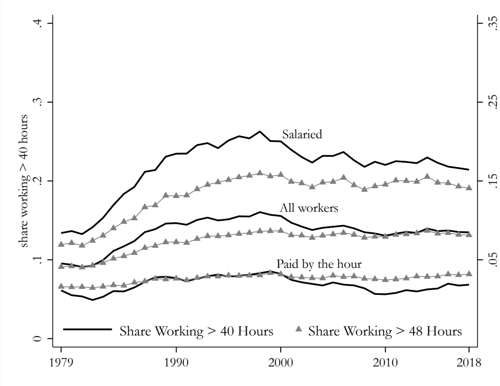
Table C.1: Structural Break in Time Series of Long-Hours Employees and Usual Hours

	Years in Sample	Years in in Trim. Sample	Estimated Break Year	P-Value
% Work Long Hours	1979-2018	1985-2013	1995	0.0000
Usual Work Hours	1979-2018	1985-2013	1995	0.0000

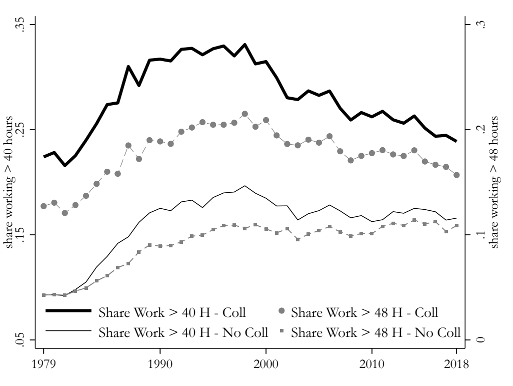
Notes: CPS - ORG 25-64 year-old male full-time salaried workers. The table reports a test for a structural break in the time-series of the share of salaried employees working long-hours and in the time series of average usual hours worked by salaried employees.

C.2 Robustness of Trends in Overtime Work

Figure C.1: Female Workers
Share Working More than 40 Hours and Share Working More than 48 Hours



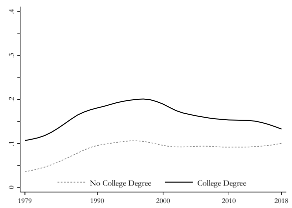
(a) All Workers



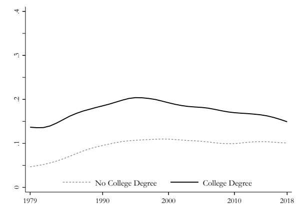
(b) Salaried by Education

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time female workers. Workers are defined to be salaried if they are not paid by the hour.

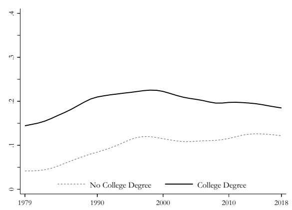
Figure C.2: Female Workers - Salaried Workers by Age Group - Share Working > 48 hours



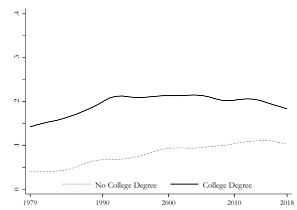
(a) 25-34 y.o.



(b) 35-44 y.o.



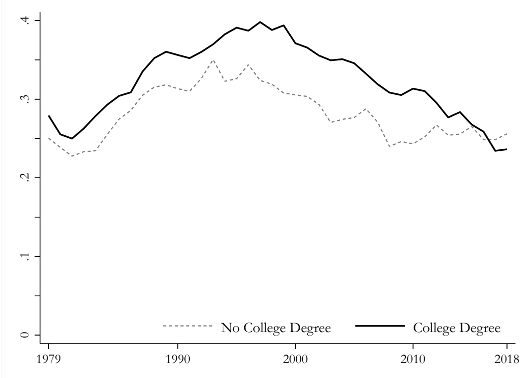
(c) 45-54 y.o.



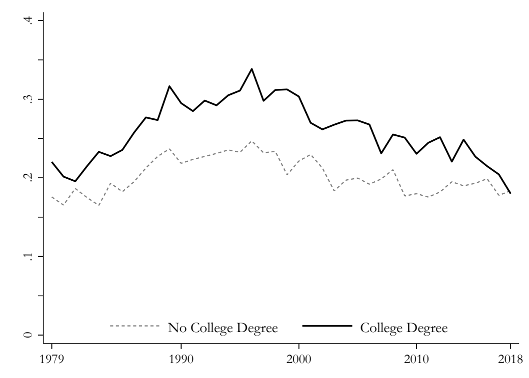
(d) 55-64 y.o.

Notes: CPS - Outgoing Rotation Groups. 25-64 year-old full-time female workers who are not paid by the hour. Each figure shows trends for college graduates and for workers without a college degree.

Figure C.3: Married and Unmarried Men - Share Working More than 48 Weekly Hours



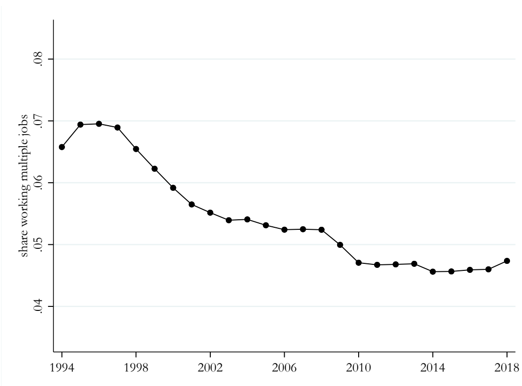
(a) Ever Married



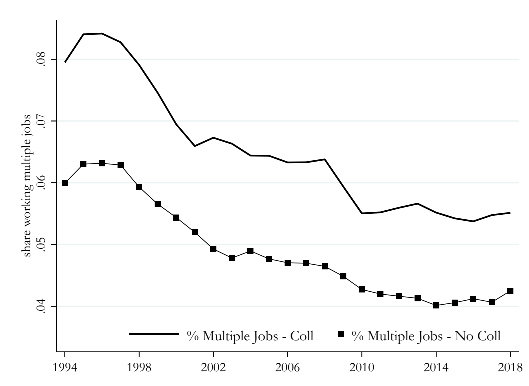
(b) Never Married

Notes: CPS - Outgoing Rotation Groups. 25-44 year-old full-time male salaried workers. I define CPS workers to be "salaried" if they are not paid by the hour.

Figure C.4: Share of Workers Holding Multiple Jobs



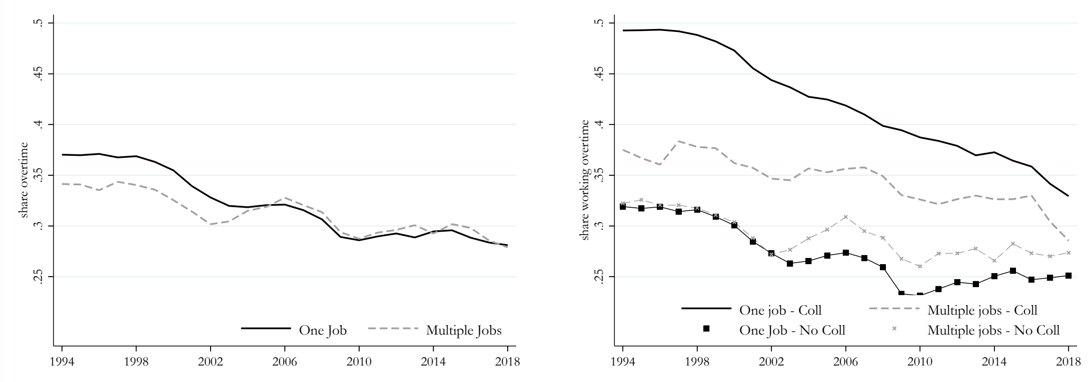
(a) All workers



(b) By Education

Notes: CPS Monthly data. 25-64 year-old full-time male workers. Data on the number of jobs held by workers are available from 1994 on.

Figure C.5: Employees Working Long Hours by Number of Jobs Held

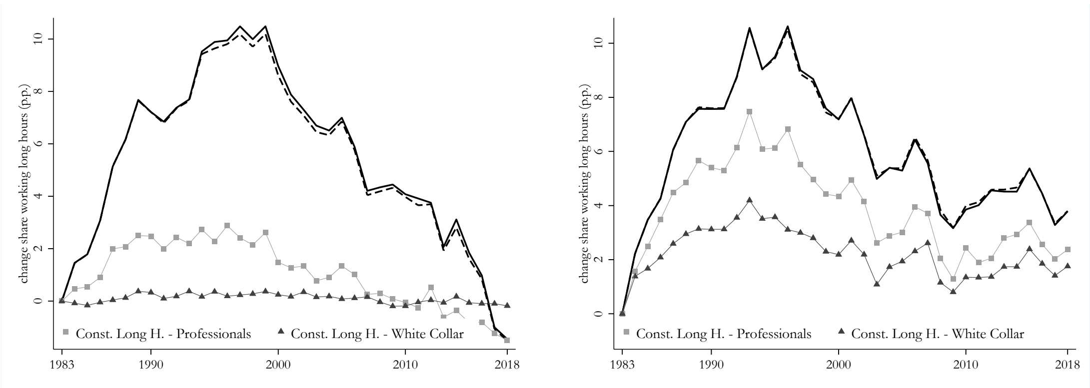


(a) All workers (b) By Education

Notes: CPS Monthly data. 25-64 year-old full-time male workers. Data on the number of jobs held by workers are available from 1994 on.

C.3 Trends in Long Hours Within Occupations

Figure C.6: The Contribution of Occupation Groups to the Trends in Long Hours



(a) College Degree

(b) No College Degree

Notes: CPS-Outgoing Rotation Groups. 25-64 years old male full-time salaried employees. A long workweek is a workweek requiring more than 48 work-hours.

C.4 Model Derivations

Workers' Optimal Choice of Work Hours

Workers i choose choose hours conditional on being on a promotion career path or on a "no promotion" career path. For workers on the "no promotion" path the utility maximization problem is

$$\max_{h_1,h_2} \left[(d_1 + c_1\eta_1)h_1 - b_i h_1^2\right] + \left[(d_1 + c_1\eta_1(1 + \theta_i h)_1))h_2 - b_i h_2^2\right] \tag{C.1}$$

The first order conditions for this utility maximization problem are

$$\text{FOC for } h_1\text{: } (d_1 + c_1\eta_1) - 2b_i h_1 + c_1\eta_1\theta_i h_2 = 0 \tag{C.2}$$

$$\text{FOC for } h_2\text{: } (d_1 + c_1\eta_1(1 + \theta_i h_1)) - 2b_i h_2 = 0 \tag{C.3}$$

Equating the left-hand sides of the two FOCs implies $h_1^{n*} = h_2^{n*}$, and using either one of the FOCs implies

$$h_t^{n*} = \frac{d_1 + c_1\eta_1}{2b_i - c_1\eta_1\theta_i} \text{ for } t = \{1, 2\} \tag{C.4}$$

For workers on the promotion path the utility maximization problem is

$$\max_{h_1,h_2} \left[(d_1 + c_1\eta_1)h_1 - b_i h_1^2\right] + \left[(d_2 + c_2\eta_1(1 + \theta_i h)_1))h_2 - b_i h_2^2\right] \tag{C.5}$$

The first order conditions are

$$\text{FOC for } h_1\text{: } (d_1 + c_1\eta_1) - 2b_i h_1 + c_1\eta_1\theta_i h_2 = 0 \tag{C.6}$$

$$\text{FOC for } h_2\text{: } (d_2 + c_2\eta_1(1 + \theta_i h_1)) - 2b_i h_2 = 0 \tag{C.7}$$

From equation C.7, $h_2 = \frac{d_2+c_2\eta_1(1+\theta_i h_1)}{2b_i}$, and substituting into equation C.6

implies

$$
\begin{aligned}
(d_1 + c_1\eta_1) - 2b_i h_1 + c_1\eta_1\theta_i \left[\frac{d_2 + c_2\eta_1(1+\theta_i h_1)}{2b_i}\right] &= 0 \\
-2b_i h_1 + \frac{c_2^2\eta_1^2\theta_i^2 - 4b_i^2}{2b_i} h_1 &= -d_1 - c_1\eta_1 - \frac{c_2\eta_1\theta_i(d_2 + c_2\eta_1)}{2b_i} \\
h_1\left(c_2^2\eta_1^2\theta_i^2 - 4b_i^2\right) &= -2b_i(d_1 + c_1\eta_1) - c_2\eta_1\theta_i(d_2 + c_2\eta_1) \\
h_1^{p*} &= \frac{2b_i(d_1 + c_1\eta_1) + c_2\eta_1) + c_2\eta_1\theta_i(d_2 + c_2\eta_1)}{(4b_i^2 - c_2^2\eta_1^2\theta_i^2)} \qquad \text{(C.8)}
\end{aligned}
$$

Using equation C.8 and substituting for h_1 in equation C.7 implies

$$
\begin{aligned}
h_2^{p*} &= \frac{d_2}{2b_i} + \frac{c_2\eta_1}{2b_i} + \frac{c_2\eta_1\theta_i}{2b_i}\left[\frac{2b_i(d_1 + c_1\eta_1) + c_2\eta_1\theta_i(d_2 + c_2\eta_1)}{(4b_i^2 - c_2^2\eta_1^2\theta_i^2)}\right] \\
&= \frac{2b_i(d_2 + c_2\eta_1) + c_2\eta_1\theta_i(d_1 + c_1\eta_1)}{(4b_i^2 - c_2^2\eta_1^2\theta_i^2)} \qquad \text{(C.9)}
\end{aligned}
$$

Workers' Selection into the Promotion Career Path

Given workers' optimal choice of work hours, the indirect utility that a worker obtains on the "no promotion" career path is

$$
\begin{aligned}
V^n(w_1^n, w_2^n, .) &= \left(w_{i1}^n h_{i1}^{n*} - b_i h_{i1}^{n*2}\right) + \left(w_{i2}^n h_{i2}^{n*} - b_i h_{i2}^{n*2}\right) \\
&= (d_1 + c_1\eta_1)h_{it}^* - b_i h_{it}^{*2} + \left[d_1 + c_1\eta_1(1+\theta_i h_{it}^*)\right] h_{it}^* - b_i h_{it}^{*2} \\
&= 2(d_1 + c_1\eta_1)h_{it}^* - 2b_i h_{it}^{*2} + c_1\eta_1\theta_i h_{it}^{*2} \\
&= 2\frac{(d_1 + c_1\eta_1)^2}{(2b_i - c_1\eta_1)} - (2b_i - c_1\eta_1\theta_i)\frac{(d_1 + c_1\eta_1)^2}{(2b_i - c_1\eta_1)^2} \\
&= \frac{(d_1 + c_1\eta_1)^2}{(2b_i - c_1\eta_1)} \qquad \text{(C.10)}
\end{aligned}
$$

Workers' indirect utility on the promotion career path is

$$\begin{aligned}
V^p(w_1^p, w_2^p, .) &= \left(w_{i1}^p h_{i1}^{p*} - b_i h_{i1}^{p*2}\right) + \left(w_{i2}^p h_{i2}^{p*} - b_i h_{i2}^{p*2}\right) \\
&= (d_1 + c_1\eta_1)h_{i1}^{p*} - b_i h_{i1}^{p*2} + \left[d_2 + c_2\eta_1(1 + \theta_i h_{i1}^{p*})\right] h_{i2}^{p*} - b_i h_{i2}^{p*2} \\
&= \frac{(d_1 + c_1\eta_1)^2 b_i + (d_2 + c_2\eta_1)^2 b_i + (d_1 + c_1\eta_1)(d_2 + c_2\eta_1)c_2\eta_1\theta_i}{(4b_i^2 - c_2^2\eta_1^2\theta_i^2)}
\end{aligned} \tag{C.11}$$

Each worker i is indifferent between the two career paths when

$$V^p(w_1^p, w_2^p, .) = V^p(w_1^p, w_2^p, .) \tag{C.12}$$

After some algebra, equation C.12 takes the form of the following quadratic equation in b_i. The unique positive root of the equation, as a function of θ_i, is the threshold preference for leisure $\bar{b}\theta_i$ such that worker i is indifferent between pursuing the promotion career path or the "no promotion" career path.

$$2b_i^2\left[(d_2 + c_2\eta_1)^2 - (d_2 + c_2\eta_1)^2\right] - b_i c_2\eta_1\theta_i\left[\right] \tag{C.13}$$

Specifically, solving C.13 yields

$$\bar{b}(\theta_i) = \frac{\left(c_2\left[(d_2 + c_2\eta_1) - (d_1 + c_1\eta_1)\right]^2 + \sqrt{\Delta(\eta_1, c_1, c_2, d_1, d_2)}\right)\eta_1\theta_i}{4\left[(d_2 + c_2\eta_1)^2 - (d_1 + c_1\eta_1)^2\right]} \tag{C.14}$$

Where

$$\begin{aligned}
\Delta(\eta_1, c_1, c_2, d_1, d_2) &= c_2^2\left[(d_2 + c_2\eta_1) - (d_1 + c_1\eta_1)\right]^4 + \\
&+ 8\left[(d_2 + c_2\eta_1)^2 - (d_1 + c_1\eta_1)^2\right]\left[(d_2 + c_2\eta_1)c_1 - c_2\right](d_1 + c_1\eta_1)c_2
\end{aligned} \tag{C.15}$$

Proofs of Propositions in Section 3.3.2

(1) $h_1^{*p} > h_1^{*n}$.

$$\frac{2b_i(d_1 + c_1\eta_1) + c_2\eta_1\theta_i(d_2 + c_2\eta_1)}{(4b_i^2 - c_2^2\eta_1^2\theta_i^2)} > \frac{d_1 + c_1\eta_1}{2b_i - c_1\eta_1\theta_i}$$

$$d_2 + c_2\eta_1 > d_1 + c_1\eta_1 \tag{C.16}$$

Employees optimally choose to work longer hours on promotion career paths as long as they can expect to experience wage gains in period 2 if they select the promotion career path even if their ability to learn on the job in period 1 is $\theta_i = 0$, that is, if $d_2 + c_2\eta_1 > d_1 + c_1\eta_1$.

(2) $h_2^{*p} > h_1^{*p}$.

$$\frac{2b_i(d_2 + c_2\eta_1) + c_2\eta_1\theta_i(d_1 + c_1\eta_1)}{(4b_i^2 - c_2^2\eta_1^2\theta_i^2)} > \frac{2b_i(d_1 + c_1\eta_1) + c_2\eta_1\theta_i(d_2 + c_2\eta_1)}{(4b_i^2 - c_2^2\eta_1^2\theta_i^2)}$$

$$(2b_i - c_2\eta_1\theta_i)(d_2 + c_2\eta_1) > (2b_i - c_2\eta_1\theta_i)(d_1 + c_1\eta_1) \tag{C.17}$$

The inequality always holds under the assumptions that $d_2 + c_2\eta_1 > d_1 + c_1\eta_1$ and that $2b_i > c_2\eta_1\theta_i$. The latter assumption is required in the model as it ensures that all employees select $h_t^* > 0$ in all career paths and in all time periods.

(3) $\frac{\Delta w^p}{w_1^p} > \frac{\Delta w^n}{w_1^n}$. On promotion career paths wages of worker i in periods $t = 1, 2$, and wage growth Δw^p are

$$w_1^p = d_1 + c_1\eta_1 \tag{C.18}$$

$$w_2^p = d_2 + c_2\eta_1(1 + \theta_i h_{i1}^{p*}) \tag{C.19}$$

So that wage growth in absolute and relative terms is, respectively,

$$\Delta w^p = [(d_2 + c_2\eta_1) - (d_1 + c_1\eta_1)] + c_2\eta_1\theta_i h_{i1}^{p*} \tag{C.20}$$

$$\frac{\Delta w^p}{w_1^p} = \frac{[(d_2 + c_2\eta_1) - (d_1 + c_1\eta_1)]}{(d_1 + c_1\eta_1)} + \frac{c_2\eta_1\theta_i}{(d_1 + c_1\eta_1)} h_{i1}^{p*} \tag{C.21}$$

On "no promotion" career paths wages of worker i in periods $t = 1, 2$, and wage growth $\Delta w^n$are

$$w_1^n = d_1 + c_1\eta_1 \tag{C.22}$$

$$w_2^n = d_1 + c_1\eta_1(1 + \theta_i h_{i1}^{n*}) \tag{C.23}$$

And wage growth between periods 1 and 2 is, in absolute terms and relative to w_1^n is, respectively

$$\Delta w^n = c_1\eta_1\theta_i h_{i1}^{n*} \tag{C.24}$$

$$\frac{\Delta w^n}{w_1^n} = \frac{c_1\eta_1\theta_i}{(d_1 + c_1\eta_1)} h_{i1}^{n*} \tag{C.25}$$

Hence, $\Delta w^p > \Delta w^n$ and $\frac{\Delta w^p}{w_1^p} > \frac{\Delta w^n}{w_1^n}$ as long as $d_2 + c_2\eta_1 > d_1 + c_1\eta_1$ and $c_2 > c_1$ given that, for every type θ_i worker, $h_{i1}^{n*} < h_{i1}^{p*}$.

(4) and (5) $\frac{\partial\left[\Delta w^p / w_1^p\right]}{\partial h_{i1}} > \frac{\partial\left[\Delta w^n / w_1^n\right]}{\partial h_{i1}}$ and $\frac{\partial \Delta w^p}{\partial h_{i1}} > \frac{\partial \Delta w^n}{\partial h_{i1}}$. The two results follow directly from taking the partial derivatives of the equations above, under the assumption that $c_2 > c_1$.

(6) $\bar{b}(\theta_i)$ is a linearly increasing function of θ_i. See equation C.14.

(7) $\frac{\partial \bar{b}(\theta_1)}{\partial d_2} > 0$ and $\frac{\partial \bar{b}(\theta_1)}{\partial c_2} > 0$.

C.5 Returns to Long Hours- Robustness Checks

Table C.2: Dynamic Returns of Working Long Hours - Control for Current Hours

	(1) All Employees 25-55 y.o		(2) Salaried 25-55 y.o		(3) Hourly Paid 25-55 y.o		(4) Salaried 25-44 y.o		(5) Hourly Paid 25-44 y.o	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
$\varphi^{1981-85}$	0.570	0.304	0.622	0.464	0.509	0.216	0.622	0.304	0.513	0.148
	(0.022)	(0.035)	(0.033)	(0.046)	(0.029)	(0.049)	(0.038)	(0.046)	(0.034)	(0.053)
$\varphi^{1986-90}$	0.572	0.302	0.629	0.468	0.506	0.208	0.630	0.309	0.513	0.142
	(0.022)	(0.035)	(0.033)	(0.046)	(0.029)	(0.049)	(0.037)	(0.046)	(0.034)	(0.053)
$\varphi^{1991-95}$	0.587	0.308	0.638	0.474	0.523	0.213	0.639	0.313	0.535	0.148
	(0.022)	(0.035)	(0.033)	(0.046)	(0.030)	(0.049)	(0.038)	(0.045)	(0.034)	(0.053)
$\varphi^{1996-2000}$	0.597	0.320	0.648	0.485	0.533	0.225	0.651	0.326	0.547	0.164
	(0.023)	(0.035)	(0.033)	(0.046)	(0.030)	(0.049)	(0.038)	(0.045)	(0.035)	(0.053)
$\varphi^{2001-05}$	0.556	0.286	0.601	0.442	0.494	0.195	0.584	0.269	0.519	0.149
	(0.023)	(0.035)	(0.034)	(0.047)	(0.031)	(0.049)	(0.039)	(0.045)	(0.036)	(0.053)
$\varphi^{2006-10}$	0.549	0.268	0.607	0.438	0.476	0.166	0.571	0.244	0.496	0.113
	(0.024)	(0.035)	(0.035)	(0.047)	(0.032)	(0.050)	(0.041)	(0.046)	(0.038)	(0.055)
$\varphi^{2011-15}$	0.540	0.251	0.599	0.429	0.464	0.143	0.560	0.238	0.487	0.088
	(0.026)	(0.036)	(0.037)	(0.048)	(0.034)	(0.051)	(0.044)	(0.046)	(0.041)	(0.056)
N	50795	50795	20181	20181	30614	30614	14648	14648	23266	23266
R^2	0.47	0.09	0.57	0.20	0.36	0.06	0.56	0.21	0.34	0.07
adj. R^2	0.47	0.09	0.57	0.20	0.36	0.05	0.56	0.21	0.34	0.07

Notes: Control variables include a college-graduate dummy, a quadratic function of age and the full set of interactions between these variables and between each variable and time. The regressions control for current log-hours as in Michelacci & Pijoan-Mas (2011).

C.6 Permanent and Transitory Inequality

The Heathcote, Storesletten & Violante (2010) Model

I estimate the evolution over time of permanent wage inequality and wage volatility by following strictly Heatcote, Storesletten and Violante (2010). They estimated the two components of wage inequality using PSID data from 1968 to 2000. The only differences between my estimation and theirs regard the sample selection.

In this section I summarize the methodology and identification assumptions proposed by Heathcote, Storesletten & Violante (2010). Additional details can be found in Heathcote, Storesletten & Violante (2008). In addition, I derive all the theoretical moments and list all the empirical moments that I use in the estimation. It is worth noting that, being the model overidentified, it is possible to estimate the variance of the persistent component of wage residuals also in years for which PSID data are not available as the survey became biennial from 1998.

Statistical Model for Wage Residuals Individuals i of age j at time t. Wage residuals $y_{i,j,t}$

$$y_{i,j,t} = \eta_{i,j,t} + \nu_{i,j,t} + \tilde{\nu}_{i,j,t} \tag{C.26}$$

$$\eta_{i,j,t} = \rho\eta_{i,j,t-1} + \omega_{i,j,t} \tag{C.27}$$

- $\tilde{\nu}_{i,j,t} \sim \left(0, \lambda^{\tilde{\nu}}\right)$

  Transitory component capturing measurement error. Ignored.

- $\nu_{i,j,t} \sim (0, \lambda^{\nu})$

  Transitory individual productivity shock.

- $\eta_{i,j,t}$

  Persistent component of labor productivity.

- $\omega_{i,j,t} \sim (0, \lambda^{\omega})$

Persistent individual productivity shock.

- For all t, at age $j = 0$ (25-34 years old) $\eta_{i,1,t}$ drawn from time invariant distribution with variance λ^{η}.

  No cohort-specific components of labor productivity.

- $\omega_{i,j,t}$, $\nu_{i,j,t}$, $\tilde{\nu}_{i,j,t}$, $\eta_{i,1,t}$

  Orthogonal to each other and i.i.d. across population

- For all ages j, at $t = 1$ (for me year 1979) the distribution of labor productivity is assumed to be in steady state with variances $\{\lambda^{\tilde{\nu}}, \lambda_1^{\nu}, \lambda_1^{\omega}, \lambda^{\eta}\}$.

- Time varying variances: $\lambda_1^{\nu}, \lambda_1^{\omega}$

  Time constant variances: $\lambda^{\tilde{\nu}}, \lambda^{\eta}.\lambda^{\tilde{\nu}}$ not estimated.

Given my data, I need to estimate the following 70 parameters:

$\theta = \{\rho, \lambda^{eta}, \lambda^{\nu}_{1979}, ..., \lambda^{\nu}_{1997}, \lambda^{\nu}_{1999}, \lambda^{\nu}_{2001}, ..., \lambda^{\nu}_{2017}, \lambda^{\omega}_{1979}, ..., \lambda^{\omega}_{1997}, \lambda^{\omega}_{1998}, \lambda^{\omega}_{1999}, ..., \lambda^{\omega}_{2017}\}$

The variance of persistent productivity shocks can be estimated for unobserved years as well.

Identification and Observations used Let individuals enter the market at age 1 = 25-34.

- Identify ρ and λ^{η}

  - Moments 1

    Covariance between t and (t+1) of residual wages among individuals being of age 1 (25-34) in t. The corresponding empirical moment can be found for all years $t = 1979, 1980, ..., 1996$.

$$m^1_{t,t+1} = E\left[\left(\eta_{i,1,t} + \nu_{i,1,t}\right)\left(\eta_{i,2,t+1} + \nu_{i,2,t+1}\right)\right] = \rho\lambda^{\eta}$$

    Use sample of individuals aged 1 in t and 2 in (t+1) and observed in both years

- Moments 2

  Covariance between t and (t+2) of residual wages among individuals being of age 1 (25-34) in t. The corresponding empirical moment can be found for all years $t = 1979, 1980, ..., 1995, 1997, 1999, 2015$.

$$m^1_{t,t+2} = E\left[(\eta_{i,1,t} + \nu_{i,1,t})\,(\eta_{i,3,t+2} + \nu_{i,3,t+2})\right] = \rho^2\lambda^\eta$$

  Use sample of individuals aged 1 in t and 3 in (t+2) and observed in both years.

- Moments 3

  Covariance between t and (t+3) of residual wages among individuals being of age 1 (25-34) in t. The corresponding empirical moment can be found for all years $t = 1979, 1980, ..., 1994, 1996$.

$$m^1_{t,t+3} = E\left[(\eta_{i,1,t} + \nu_{i,1,t})\,(\eta_{i,4,t+3} + \nu_{i,4,t+3})\right] = \rho^3\lambda^\eta$$

  Use sample of individuals aged 1 in t and 4 in (t+3) and observed in both years.

- Moments 4

  Covariance between t and (t+4) of residual wages among individuals being of age 1 (25-34) in t. The corresponding empirical moment can be found for all years $t = 1979, 1980, ..., 1995, 1997, ..., 2013$.

$$m^1_{t,t+4} = E\left[(\eta_{i,1,t} + \nu_{i,1,t})\,(\eta_{i,5,t+4} + \nu_{i,5,t+4})\right] = \rho^4\lambda^\eta$$

  Use sample of individuals aged 1 in t and 5 in (t+4) and observed in both years.

• Identify λ^ν_t

Variance in t of wage residuals among individuals of age 1 (25-34) in time t.

$$m_{t,t}^{1} = E\left[(\eta_{i,1,t} + \nu_{i,1,t})^2\right] = \lambda^{\eta} + \lambda_t^{\nu}$$

Knowing λ^{η}, each year specific variance identifies the year specific variance of the transitory productivity shock. The corresponding empirical moment can be found for all years $t = 1979, 1980, ..., 1997, 1999, ...2017$.

For each t, use sample of individuals aged 1 (25-34) in t.

- Identify λ_t^{ω}

- Moments 1

Variance in t of wage residuals among individuals of age 2 (26-35) in time t.

$$m_{t,t}^{2} = E\left[(\eta_{i,2,t} + \nu_{i,2,t})^2\right] = \rho^2\lambda^{\eta} + \lambda_t^{\omega} + \lambda_t^{\nu}$$

Knowing all the other parameters, each year specific variance identifies the year specific variance of the persistent productivity shock for all observable years.

For each t, use sample of individuals aged 2 (26-35) in t.

- Moments 2

Variance in t of wage residuals among individuals of age 3 (27-36) in time t.

$$m_{t,t}^{3} = E\left[(\eta_{i,3,t} + \nu_{i,3,t})^2\right] = \rho^4\lambda^{\eta} + \rho^2\lambda_{t-1}^{\omega} + \lambda_t^{\omega} + \lambda_t^{\nu}$$

For each $t = 1980, 1981, ..., 1997, 1999, ..., 2017$, use sample of individuals aged 3 (27-36) in t.

- Moments 3

Variance in t of wage residuals among individuals of age 4 (28-37) in time t.

$$m^4_{t,t} = E\left[(\eta_{i,4,t} + \nu_{i,4,t})^2\right] = \rho^6\lambda^\eta + \rho^4\lambda^\omega_{t-2} + \rho^2\lambda^\omega_{t-1} + \lambda^\omega_t + \lambda^\nu_t$$

For each $t = 1981, 1982, ..., 1997, 1999, ..., 2017,$ use sample of individuals aged 4 (28-37) in t.

- Moments 4

Variance in t of wage residuals among individuals of age 5 (29-38) in time t.

$$m^5_{t,t} = E\left[(\eta_{i,5,t} + \nu_{i,5,t})^2\right] = \rho^8\lambda^\eta + \rho^6\lambda^\omega_{t-3} + \rho^4\lambda^\omega_{t-2} + \rho^2\lambda^\omega_{t-1} + \lambda^\omega_t + \lambda^\nu_t$$

For each $t = 1982, 1983, ..., 1997, 1999, ..., 2017,$ use sample of individuals aged 5 (29-38) in t.

- Moments 5 to 30

Variance in t of wage residuals among individuals of age a 6 (30-39) to 31 (55-64) in time t.

$$m^a_{t,t} = \rho^{(2a-2)}\lambda^\eta + \left(\sum_{k=1}^{(a-2)} \rho^{2k}\lambda^\omega_{t-k}\right) + \lambda^\omega_t + \lambda^\nu_t$$

- Additional Moments

- Moments 1a

Covariance between t and (t+1) of residual wages among individuals being of age 3 (27-36) in t. The corresponding empirical moment can be found for all years $t = 1980, ..., 1996$.

$$m^3_{t,t+1} = E\left[(\eta_{i,3,t} + \nu_{i,3,t})(\eta_{i,4,t+1} + \nu_{i,4,t+1})\right] = \rho^5\lambda^\eta + \rho^3\lambda^\omega_{t-1} + \rho\lambda^\omega_t$$

Use sample of individuals aged 3 in t and 4 in (t+1) and observed in both years

- Moments 1b

  Covariance between t and (t+2) of residual wages among individuals being of age 3 (27-36) in t. The corresponding empirical moment can be found for all years $t = 1980, ..., 1995, 1997, 1999, 2015$.

$$m^3_{t,t+2} = E\left[(\eta_{i,3,t} + \nu_{i,3,t})(\eta_{i,5,t+2} + \nu_{i,5,t+2})\right] = \rho^6\lambda^\eta + \rho^4\lambda^\omega_{t-1} + \rho^2\lambda^\omega_t$$

  Use sample of individuals aged 3 in t and 5 in (t+2) and observed in both years.

- Moments 1c

  Covariance between t and (t+3) of residual wages among individuals being of age 3 (27-36) in t. The corresponding empirical moment can be found for all years $t = 1980, ..., 1994, 1996$.

$$m^3_{t,t+3} = E\left[(\eta_{i,3,t} + \nu_{i,3,t})(\eta_{i,6,t+3} + \nu_{i,6,t+3})\right] = \rho^7\lambda^\eta + \rho^5\lambda^\omega_{t-1} + \rho^3\lambda^\omega_t$$

  Use sample of individuals aged 3 in t and 6 in (t+3) and observed in both years.

- Moments 1d

  Covariance between t and (t+4) of residual wages among individuals being of age 3 (27-36) in t. The corresponding empirical moment can be found for all years $t = 1980, ..., 1995, 1997, ..., 2013$.

$$m^3_{t,t+4} = E\left[(\eta_{i,3,t} + \nu_{i,3,t})(\eta_{i,7,t+4} + \nu_{i,7,t+4})\right] = \rho^8\lambda^\eta + \rho^6\lambda^\omega_{t-1} + \rho^4\lambda^\omega_t$$

  Use sample of individuals aged 3 in t and 7 in (t+4) and observed in both years.

- Moments 2a

  Covariance between t and (t+1) of residual wages among individuals being of age 4 (28-37) in t. The corresponding empirical moment can be found for all years $t = 1981, ..., 1996$.

$$m^4_{t,t+1} = E\left[(\eta_{i,4,t} + \nu_{i,4,t})(\eta_{i,5,t+1} + \nu_{i,5,t+1})\right] = \rho^7\lambda^\eta + \rho^5\lambda^\omega_{t-2} + \rho^3\lambda^\omega_{t-1} + \rho\lambda^\omega_t$$

Use sample of individuals aged 4 in t and 5 in (t+1) and observed in both years

- Moments 2b

  Covariance between t and (t+2) of residual wages among individuals being of age 4 (28-37) in t. The corresponding empirical moment can be found for all years $t = 1981, ..., 1995, 1997, 1999, 2015$.

$$m^4_{t,t+2} = E\left[\left(\eta_{i,4,t} + \nu_{i,4,t}\right)\left(\eta_{i,6,t+2} + \nu_{i,6,t+2}\right)\right] = \rho^8\lambda^\eta + \rho^6\lambda^\omega_{t-2} + \rho^4\lambda^\omega_{t-1} + \rho^2\lambda^\omega_t$$

  Use sample of individuals aged 4 in t and 6 in (t+2) and observed in both years.

- Moments 2c

  Covariance between t and (t+3) of residual wages among individuals being of age 4 (28-37) in t. The corresponding empirical moment can be found for all years $t = 1981, ..., 1994, 1996$.

$$m^4_{t,t+3} = E\left[\left(\eta_{i,4,t} + \nu_{i,4,t}\right)\left(\eta_{i,7,t+3} + \nu_{i,7,t+3}\right)\right] = \rho^9\lambda^\eta + \rho^7\lambda^\omega_{t-2} + \rho^5\lambda^\omega_{t-1} + \rho^3\lambda^\omega_t$$

  Use sample of individuals aged 4 in t and 7 in (t+3) and observed in both years.

- Moments 2d

  Covariance between t and (t+4) of residual wages among individuals being of age 4 (28-37) in t. The corresponding empirical moment can be found for all years $t = 1981, ..., 1995, 1997, ..., 2013$.

$$m^4_{t,t+4} = E\left[\left(\eta_{i,4,t} + \nu_{i,4,t}\right)\left(\eta_{i,8,t+4} + \nu_{i,8,t+4}\right)\right] = \rho^{10}\lambda^\eta + \rho^8\lambda^\omega_{t-2} + \rho^6\lambda^\omega_{t-1} + \rho^4\lambda^\omega_t$$

- Use sample of individuals aged 4 in t and 8 in (t+4) and observed in both years.

- Moments 3

  Covariance between t and (t+1) of residual wages among individuals being of age $a = 5, 6, ...$ in t. The corresponding empirical moment can be found for all years $t = 1979 + a - 2, ..., 1996$.

$$m^a_{t,t+1} = E\left[(\eta_{i,a,t} + \nu_{i,a,t})\left(\eta_{i,a+1,t+1} + \nu_{i,a+1,t+1}\right)\right] = \rho^{(2a-1)}\lambda^\eta + \sum_{k=1}^{a-2}\rho^{2k+1}\lambda^\omega_{t-k} + \rho\lambda^\omega_t$$

Use sample of individuals aged a in t and $a + 1$ in (t+1) and observed in both years.

- Moments 4

  Covariance between t and (t+2) of residual wages among individuals being of age $a = 5, 6, ...$ in t. The corresponding empirical moment can be found for all years $t = 1979 + a - 2, ..., 1997, 1999, ..., 2015$.

$$m^a_{t,t+2} = E\left[(\eta_{i,a,t} + \nu_{i,a,t})\left(\eta_{i,a+2,t+2} + \nu_{i,a+2,t+2}\right)\right] = \rho^{(2a)}\lambda^\eta + \sum_{k=1}^{a-2}\rho^{2k+2}\lambda^\omega_{t-k} + \rho^2\lambda^\omega_t$$

Use sample of individuals aged a in t and $a + 2$ in (t+2) and observed in both years.

- Moments 5

  Covariance between t and (t+3) of residual wages among individuals being of age $a = 5, 6, ...$ in t. The corresponding empirical moment can be found for all years $t = 1979 + a - 2, ..., 1994, 1996$.

$$m^a_{t,t+3} = E\left[(\eta_{i,a,t} + \nu_{i,a,t})\left(\eta_{i,a+3,t+3} + \nu_{i,a+3,t+3}\right)\right] = \rho^{(2a+1)}\lambda^\eta + \sum_{k=1}^{a-2}\rho^{2k+3}\lambda^\omega_{t-k} + \rho^3\lambda^\omega_t$$

- Use sample of individuals aged a in t and $a + 3$ in (t+3) and observed in both years.

- Moments 6

  Covariance between t and (t+4) of residual wages among individuals being of age $a = 5, 6, ...$ in t. The corresponding empirical moment can be found for all years $t = 1979 + a - 2, ..., 1995, 1997, ..., 2013$.

$$m^a_{t,t+4} = E\left[(\eta_{i,a,t} + \nu_{i,a,t})\left(\eta_{i,a+4,t+4} + \nu_{i,a+4,t+4}\right)\right] = \rho^{(2a+2)}\lambda^\eta + \sum_{k=1}^{a-2}\rho^{2k+4}\lambda^\omega_{t-k} + \rho^4\lambda^\omega_t$$

Use sample of individuals aged a in t and $a + 4$ in (t+4) and observed in both years.

Sample Moments and Estimation I generate "rotating" age groups: 1 = 25-34, 2 = 26-35, ... until last group = 55-64.

I report below some of the empirical moments used in the estimation. The construction of the other required empirical moments straightforwardly follows from the definition of the theoretical moments needed to identify the different parameters and listed above

- Identify ρ and λ^{η}

  - Empirical Moment 1. Let
    $I = \{i : age_{i,1979} \in \{25, ..., 34\} \,\&\, age_{i,1980} \in \{26, ..., 35\}\}$
    And i observed in 1979 & 1980

$$\hat{m}^1_{1,2} = \frac{1}{N_I} \sum_{i \in I} \hat{y}_{i,1,1979} \hat{y}_{i,2,1980}$$

  - Empirical Moment 2. Let
    $J = \{i : age_{i,1979} \in \{25, ..., 34\} \,\&\, age_{i,1981} \in \{27, ..., 36\}\}$
    And i observed in 1979 & 1981.

$$\hat{m}^1_{1,3} = \frac{1}{N_J} \sum_{i \in J} \hat{y}_{i,1,1979} \hat{y}_{i,3,1981}$$

- Identify λ^{ν}_t
  Let $I_t = \{i : age_{i,t} \in \{25, ..., 34\}$ & i observed in& $t\}$
  Empirical Moments, for all $t \in \{1979, 1980, ..., 1997, 1999, 2001, ..., 2017\}$

$$\hat{m}^t_{1,1} = \frac{1}{N_{I_t}} \sum_{i \in I_t} \hat{y}^2_{i,1,t}$$

- Identify λ^{ω}_t

  - Empirical Moments 1. Let $J_t = \{i : age_{i,t} \in \{26, ..., 35\} \,\&\, i \,\text{observed in}\, t\}$

Empirical Moments, for all $t \in \{1979, 1980, ..., 1997, 1999, 2001, ..., 2017\}$

$$\hat{m}^t_{2,2} = \frac{1}{N_{J_t}} \sum_{i \in I_t} \hat{y}^2_{i,2,t}$$

It is important to notice that different moments are estimated on different samples.

The estimation follows HSV. It uses a minimum distance estimator. The minimization problem is

$$\min_{\theta} [\hat{\mathbf{m}} - \mathbf{m}]' \mathbf{I} [\hat{\mathbf{m}} - \mathbf{m}]$$

$\hat{\mathbf{m}}$ is the (62×1) vector of stacked empirical moments, $\mathbf{m}$ is the (62×1) vector of stacked theoretical moments whose relation with the parameter vector θ is described above. As in HSV, the (62×62) identity matrix I is used instead of the optimal weighting matrix. I compute standard errors by bootstrap with 500 replications.