Higher-Educated Workers' Flattening Returns to Experience

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Abstract

This paper documents the labor-earning trajectories of young workers in France since the early 1990s. Wages at labor market entry increase overall, but the higher education graduates' wage growth flattens across cohorts. The paper proposes an equilibrium model of human capital accumulation over the life cycle in which a representative firm requires labor in two different occupations, routine and complex. The complex occupation allows faster human capital accumulation. Workers sort into occupations based on initial human capital and ability to learn. The model is estimated using observed wage moments and occupation sorting over thirty years. Estimation results highlight the role of the French higher education expansion of the 1990s and 2000s in causing occupational congestion, whereby the share of higher education graduates employed in routine occupations rose, flattening their wage profiles.

Keywords: Human Capital, Returns to Experience, Occupational Sorting, Education Expansion.

JEL Classification: J24, J31

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1 Introduction

Higher education graduates usually enjoy higher starting wages and steeper wage growth throughout their career than workers who did not graduate from a higher education institution (Card (1999), Lagakos et al. (2018), Deming (2023)). This paper examines how workers' wage profiles change during an education expansion, differently by education level. It evidences both a rise in educated workers' starting wages of all workers and a slowdown in their wage growth. Moreover, it explains these apparently contradicting observations through occupational congestion, whereby the education expansion causes higher-educated workers to increasingly sort into occupations that afford a slower human capital accumulation. Their initial wage does not suffer, but returns to experience in these occupations are flat. The occupational congestion hypothesis is tested using a model of human capital accumulation over the life cycle, where wages result from the equilibrium between supply and demand. The model is estimated based on thirty years of French labor force surveys. The counterfactual analysis demonstrates the role of occupational congestion. It rules out other mechanisms, such as a decrease in highereducated workers' underlying ability or a decrease in firm demand for higher-educated workers.

The French labor market is a stark example of an education expansion: the share of higher educated individuals in the active population went from 17% in 1990 to 43% in 2020. Such a steep increase is likely to have substantial repercussions on workers' wage profiles, and understanding the underlying mechanisms matters for the public policy debate: many European countries have seen a big political push to massify higher education, but public opinions are mainly unaware of their effects on young workers' careers.

This paper is divided into two parts. The first part examines the changes in wage profiles that occurred in France between 1990 and 2020. It documents early career earnings (up to eight years post-labor market entry) of successive birth cohorts by education level. The empirical analysis distinguishes between higher education graduates (hereafter HEGs) who hold a post-secondary education degree (from two-year professional training to an eight-year PhD) and non-higher education graduates (hereafter non-HEGs) who graduated from secondary education at most. The focus on early career stems from the need to include more recent cohorts in the analysis and is supported by the empirical literature's findings that the bulk of wage growth typically occurs within this period¹ (Murphy and Welch (1990), Murphy and Welch (1992)). Using the French labor force surveys², I show that HEGs' average wage growth -returns to potential experience- declines between the 1970 and 1985 birth cohorts—meanwhile, average starting wage increases across cohorts for both education levels. I reproduce the same analysis on a panel of three graduating cohorts who entered the French labor market in 1998, 2004, and 2010^3 . In the panel, actual labor market experience is known. The analysis shows that early average wage increases for HEGs drop from 5.8% to 4.2% between the 1998 and 2010 graduating cohorts, a 1.6 percentage point loss. However, wages in the year of entry increased by 8.3%. These findings echo the decrease observed in lifetime income across cohorts in the US due to the flattening of life-cycle profiles, studied in Guvenen et al. (2017) and Guvenen et al. (2021). Manovskii and Kambourov (2005) account for this flattening in a model where the dispersion of productivity shocks to occupation increases, which drives occupational mobility. The analysis in this paper also shows changes in occupational sorting: a declining share of HEGs are employed in complex occupations. These are defined at the one-digit level in the French nomenclature as the 'highly qualified professionals' occupations.

The mechanisms driving rising starting wages and slowed-down wage growth are challenging to disentangle. Human capital theory ties wage levels and growth to workers' human capital (Becker (1962), Becker (1994)), and models of human capital accumulation have proven to fit the labor earnings distribution well (Keane and Wolpin (1997), Huggett et al. (2006)). Moreover, evidence shows that human capital is occupationspecific (Kambourov and Manovskii (2009), Yamaguchi (2012)), suggesting the declining share of HEGs employed in the complex occupation slows down human capital accumulation and wage growth. Wages are also determined in equilibrium, balancing labor supply and firm demand (Katz and Murphy (1992), Card and Lemieux (2001)).

To integrate these aspects, the second part of this paper develops a life-cycle model of human capital accumulation that incorporates occupational sorting and firm demand. Labor supply is driven by workers whose productivity depends on their human capital. Each individual worker is endowed with an initial human capital and an ability to learn

¹I show using the labor force surveys that the flattening of wage progression is also happening on longer time-periods.

²Enquêtes Emploi, produced by INSEE

 $^{^{3}}Enquêtes\ Génération,$ produced by CEREQ

or taste for learning, which both depend on their education level. Initial human capital level and taste for learning together form a worker's underlying ability -a summary measure for cognitive and non-cognitive skills, shown to influence employment and choice of occupation in Heckman et al. (2006b). The model assumes an exogenous share of highereducated workers, focusing on career choices rather than schooling decisions. This choice stems from the argument that pecuniary factors in schooling decisions remained relatively stable over the period. The French higher education expansion was spurred largely by public authorities through the construction of new institutions and enlargement of existing ones (Dupray and Moullet (2010), Elio (2023)), which relaxed non-pecuniary constraints on access to university. It is in line with the recent literature on educational decisions that highlights the role of non-pecuniary factors (D'Haultfœuille and Maurel (2013), Cassagneau-Francis (2023)) In the model, workers maximize lifetime earnings by choosing the routine or complex occupation. They accumulate human capital on the job, in the same spirit as the dual market for skill acquisition described in Rosen (1972): workers maximize on wage, and they also anticipate future human capital, which is a Cobb-Douglas function of present human capital and ability to learn. The Cobb-Douglas parameters vary by occupation; hence, routine and complex allow different human capital accumulation speeds. As a result, workers sort into occupations based on their underlying ability, a mechanism similar to Neal and Rosen (2000). If their underlying ability is high, they sort into the occupation that affords the fastest human capital growth, even if it pays a lower wage per unit of human capital.

On the demand side, a representative firm views routine and complex occupations as imperfect substitutes. Wages are equal to the marginal product, as in the canonical model of supply and demand (Katz and Murphy (1992)). Since workers optimally sort into occupations, both labor supply to the firm and wages are set at equilibrium. The threshold for underlying ability that sorts workers between occupations is endogenous. This paper combines the seminal supply and demand literature on labor markets (Katz and Murphy (1992), Card and Lemieux (2001)) with the life-cycle human capital literature (Neal and Rosen (2000), Huggett et al. (2006)) to build a comprehensive a model of human capital accumulation over the life-cycle with supply and demand equilibrium. Deming (2023) proposes a similar model, which also features a choice between working and learning, in line with Ben-Porath (1967). Here, this choice is made exogenous and enters the worker's ability to learn, allowing for further analysis by estimating the model on thirty years of data and conducting counterfactual simulations.

When an education expansion occurs (i.e., a change in the exogenous share of higher education graduates), the model is able to capture two main potential mechanisms on the supply side: changes in occupational sorting and worsening of underlying ability. The first mechanism occurs mechanically due to the overall increase in human capital brought about by the education expansion: all else being equal, the endogenous threshold for sorting into the high returns human capital occupation rises, resulting in occupational congestion: a lower share of higher educated workers sort into this occupation. The second mechanism stems from the changes in education quality or selection that may occur alongside an education expansion: the skills or ability of educated workers could decline, either because the quality of education deteriorates (e.g., as higher education institutions face reduced resources per student), or if entry standards are lowered to accommodate a larger student body. This skill reduction can affect labor market outcomes immediately, as new graduates enter with lower initial human capital, and it may also slow future human capital accumulation due to a reduced ability to learn. On the demand side, technological change can influence occupational sorting and human capital accumulation rates, regardless of the education expansion, by shifting the demand for skills across occupations.

The model estimation allows the testing of all three mechanisms: occupational congestion, worsening underlying ability, and technological change. The model estimation uses the French labor force surveys. The model is estimated separately over ten threeyear periods, from 1991-1993 to 2018-2020. The results indicate a decline in underlying ability: average human capital at labor market entry decreases for all workers, and the variance of initial human capital rises for HEGs but drops for non-HEGs. These findings are consistent with a theory of reduced selectivity in higher education during an education expansion. However, learning ability is not affected: both its mean and variance are constant over time. On the demand side, evidence suggests complex-biased technological change favoring the complex occupation.

Counterfactual analyses are conducted by holding specific parameters at their 1991-1993 values while allowing others to vary as estimated, then calculating the equilibrium in subsequent years. They show that the exogenous increase in the HEG share is the sole driver of occupational congestion, leading to slower wage growth. The worsening of underlying ability has a counteracting effect on flattening wage progression. Since initial human capital drops over time, wages at labor market entry are pushed downwards, which mechanically steepens wage growth. Complex-biased technological change boosts both initial and final wages within the complex occupation but does not offset the flattening of wage progression for HEGs.

This paper makes two important points. First, it shows that HEGs in France know a steeper wage progression than non-HEGs, but also that their wage progression has flattened since the 1990s. Second, it offers a compelling explanation for these facts: the education expansion creates over-supply compared to firm demand, which results in occupational congestion and wage growth slowdown. These have important public policy implications, as the increase in the supply of HEGs in France was primarily driven by a massive construction of new universities and expansion of existing ones decided by French state policy-makers in the 1980s and 1990s(Verdugo (2014), Elio (2023)). This paper shows that demand for skills does not automatically follow an increase in supply. It also enjoins informing young individuals about their prospects: high wages at labor market entry do not necessarily transform into a steep wage progression in an education expansion.

The wage growth slowdown evidenced here is related to the flattening of life-cycle earnings in the US already identified by Manovskii and Kambourov (2005), Guvenen et al. (2017) and Guvenen et al. (2021). It also relates to the 'scarring effect' literature (Oreopoulos et al. (2012), Gaini et al. (2013), von Wachter (2020), Rothstein (2021)), which studies young higher educated workers' wage trajectories through the prism of the business cycle, and generally concludes that workers who enter the labor market during a recession sustain persistent losses both in employment rates and wage levels. Also, on the demand side, Beaudry et al. (2014) and Beaudry et al. (2015) show wage profiles have flattened for college graduates in the US and argue it is consistent with a structural decline in the demand for cognitive skills. The present paper offers a complementary analysis both to the scarring effect and the skill demand decline hypotheses, by showing that the French education expansion (i.e. the supply side) is the primary driver of young graduates' flattening wage profiles. Lastly, this study is related to other empirical studies of the French labor market. Verdugo (2014) shows the wage structure in France compressed due to the 1990s education expansion. This paper explores a similar compression in the wage dynamics of cohorts. Argan et al. (2022) and Argan and Gary-Bobo (2023) observe the same flattening returns to experience for young HEGs and conclude it is more likely to be due to the growth in the number of university graduates.

Section 2 presents empirical facts, Section 3 develops the model, Section 4 the results from its estimation and counterfactual analysis, and Section 5 concludes.

2 Empirical Facts

Using two datasets, one cross-section representative of the French population and one panel that follows school leavers in their early career, I quantify the changes in wage profiles by education level and occupation. Using both the cross-section and the panel data, I find both an increase in starting wage and a flattening of wage progression for HEGs.

2.1 The Data

This section uses two datasets to study wage profiles: the first is the *Enquêtes Emplois*, produced by INSEE, the French Institute for Statistics and Economic Studies (hereafter referred to as the EE cross-section), and the second is the *Enquêtes Générations*, a survey conducted by CEREQ, the Centre for Study and Research on Qualifications (hereafter referred to as the EG panel). The two datasets are complementary: the EE cross-section is a large and representative survey of French workers, while the EG panel has a smaller scope but follows individuals through time.

The EE cross-section is a yearly national labor force survey that has run since 1950. This paper uses the years 1990 to 2020^4 . It surveys a representative sample of French residents between the ages of 15 and 89. The main variables I use from this survey are individual age, education level, employment status, monthly wage, and occupation.

The EG panel is a survey that follows a graduation cohort over the first years of their professional lives. Every six years, the CEREQ surveys a representative sample of school

⁴Starting in 2003, the survey runs every trimester, but I do not exploit this dimension here. In the most recent version of the survey, respondents are surveyed for six consecutive trimesters, meaning we may be able to follow individuals from one year to the next, but not for longer. I therefore treat the data as a cross-section in the analysis.

leavers at different education levels, from high school dropouts to Ph.D. graduates. The surveys used in this paper cover three cohorts who left school in 1998, 2004, and 2010. The analysis refers to the cohort who left school and entered the labor market in year X as the X cohort. Each cohort is surveyed for up to eight years after they leave school. As such, the EG panel provides a comprehensive outlook of early career outcomes in the French labor market between the end of the 1990s and the 2010s. It also lets us observe actual labor market experience, in addition to the same variables available in the EE cross-section⁵. The dataset is an unbalanced panel: each observation corresponds to an individual's labor force status (employment or unemployment) over a given period, referred to as a spell.

Starting in 2008, the higher education system in France aligned with other EU countries: students finish secondary education at 18 years old and can choose to enter higher education to complete 2 (professional training), 3 (bachelor), 5 (master), or 8 (PhD) year degrees. An individual who has completed any of these degrees is recorded as a higher education graduate (HEG) here. A short higher education graduate (short HEG) has a degree that takes less than 4 years to complete, and a long higher education graduate (long HEG) studied for 4 years or more⁶. For most of the analysis, workers are split between HEGs and non-HEGs⁷. The EE cross section offers compelling proof of the French higher education expansion: in 1990, only 17% of the active population held a higher education degree, and in 2020, 43% do. Figure 7 in Appendix B details this change over time. As expected, it shows that the increase in the share of higher education graduates is even more striking among the young (less than 30 and 40 years old) active population.

2.2 Wage Profiles by Education Level

To measure young workers' returns to potential experience, I first use the *Enquêtes Emploi* cross-section. Given that the EE cross-section covers the years 1990 to 2020, the maximum period to study a cohort's wage profile is 30 years. Only the cohort that entered the labor market in 1990 allows such a period of time. The analysis must find a balance between the number of cohorts and the wage profile length: a long time span

 $^{^5\}mathrm{Appendix}$ A details the data cleaning procedure and shows descriptive statistics on the variables of interest.

⁶Before the European harmonization, the French education system offered 4-year degrees.

⁷This is the most common distinction in the literature on the returns to skills on the French labor market, see Verdugo (2014), Patel (2020)

offers a complete overview of each cohort's wage profile, but a shorter time span means more cohorts can be included. Given that wage profiles are generally concave and most of the wage growth occurs early in the career, the preferred period is eight years in the analysis, meaning the wage profiles are computed over the first eight years on the labor market. This choice allows for a profile of wage trajectories for nineteen birth cohorts, from the cohort born in 1970 to the cohort born in 1988⁸. It also means cohorts in the EE cross-section and the EG panel are match.

Since actual experience is unknown in the EE cross-section, I set the labor market entry age to 20 years old for a non-HEG and 24 years old for a HEG⁹. Potential experience is computed as the difference between current age and age at labor market entry. Returns to potential experience are measured with the following equation, estimated by birth cohort c by OLS:

$$\log w_{it} = \sum_{e \in \{l,h\}} \mathbb{1}_{[e_i=e]} \left(\alpha^{ce} + \beta^{ce} potexp_{it} \right) + \gamma^c X_{it} + \epsilon_{it}.$$
(1)

potexp_{it} $\in \{0, 1, ..., 8\}$ is individual *i*'s potential experience in year *t*, and X_{it} is a set of time-varying fixed effects that includes dummies for gender, whether the individual lives in an urban area and part-time. Intercept α^{ce} is the average log wage at 24 and slope β^{ce} the average wage increase for each additional year of potential experience. Both are both measured at the birth cohort *c* and education level *e*. Individual's education level e_i can be nHEG if they do not have a higher education degree and HEG if they do. Birth cohorts *c* go from 1970 (the earliest cohort observed at 20 in the data that starts in 1990) to 1988 (the latest cohort observed at 32 in the data that ends in 2020).

Equation 1 is related to the Mincerian framework (Mincer (1974)) but relaxes the additivity assumption between experience and schooling that is usual in Mincerian estimations of returns to schooling. It is a framework that is now commonly used (for example in Connolly and Gottschalk (2006), also see Heckman et al. (2008), Bhuller et al. (2017) for a discussion of the Mincerian framework's limitations), because it affords more flexibility to measure returns to experience by education level. Since equation (1) is estimated by cohort, the empirical strategy suffers from the age-time-cohort identification

⁸See Appendix A

⁹These are the averages observed in the EG panel, where we observe school-leaving age.

problem¹⁰, which arises because because age, time and cohort are linearly dependent. As a consequence, from the sole estimation of (1) on two separate cohorts c and c', we cannot tell if differences in $(\alpha^{ce}, \beta^{ce})$ and $(\alpha^{c'e}, \beta^{c'e})$ are due to time effects (e.g. changes in the labor demand from firms), or cohort effects (e.g. changes in cohorts' human capital). In the analysis that follows, we can only interpret $(\alpha^{ce}, \beta^{ce})_c$ as the average initial wage and average wage progression. We will need the model outlined in section 3 to disentangle time and cohort effects.

The results from the estimation of equation (1) on birth cohorts 1970 to 1988 are plotted in Figure 1. The left panel shows intercept α^{ce} , and the right panel shows returns β^{ce} . There are three things to note from Figure 1. First, higher education graduates generally benefit from higher initial average wage and returns to potential experience than non-graduates. Second, higher education graduates' average wage at 24 (the intercept) increases over time, while their returns to experience (the slope) change non-monotonically: they increase between birth cohorts 1970 and 1972, then fall and pick up again starting at birth cohort 1985. Third, non-graduates's average wage at 24 is U-shaped, while their returns to experience increase until birth cohort 1987 and then fall.



Figure 1: Wage profiles by education level - EE cross section

🕶 Higher Educ. 👱 No Higher Educ.

Notes: Source: EE cross-section. Author's own calculations from OLS estimation of equation (1): $\log w_{it} = \sum_{e \in \{l, h\}} \mathbb{1}_{[e_i=e]} (\alpha^{ce} + \beta^{ce} potexp_{it}) + \gamma^c X_{it} + \epsilon_{it}$. by cohort over 8 years. For comparison with the EG panel, the vertical dotted lines refer to the average birth year of the 1998, 2004, and 2010 EG cohorts, with and without a higher education degree.

 $^{^{10}}$ See Schulhofer-Wohl (2018) for an extensive review

Figure 1 plots wage profiles over the first eight years after presumed labor market entry. As a robustness check, Figures 8 and 9 in Appendix B plot wage profiles over 15 and 22 years of career. They span fewer cohorts than the main analysis but essentially tell the same story: initial average wage rises for both education levels, while wage progression flattens for HEGs and is bell-shaped for non-HEGs.

In summary, both the main analysis and the robustness checks show that starting wages increased overall for both education levels, but returns to experience did not, and higher education graduates from the birth cohorts 1976 to 1985 are worse off than their elder peers.

A significant drawback of the analysis run using equation (1) is that it does not account for the timing of labor market entry. Higher education graduates and non-graduates enter the labor market at different ages because the former study for at least two more years than the latter. Among higher education graduates, there is also substantial heterogeneity as to when each individual entered the labor market, depending on how long they studied (from 2 to 8 years). If entry in the labor market occurs at a later age for younger cohorts, then Figure 1 would not be comparing wage progression at the same stages of career across cohorts. Besides, the analysis also misses periods of unemployment by using potential experience instead of experience, which may bias the slope coefficient in regression (1). To ensure the conclusions from Figure 1 are valid, I supplement the analysis by estimating a similar equation to (1) on the *Enquêtes Génération* panel, in which the year of entry of each individual and actual labor market experience are both known for three graduation cohorts: 1998, 2004 and 2010.

A very similar equation to (1) is estimated on the *Enquêtes Génération* panel by OLS:

$$\log w_{it} = \sum_{e \in \{l,h\}} \mathbb{1}_{[e_i=e]} \left(\alpha^{ce} + \beta^{ce} exp_{it} \right) + \gamma^c X_{it} + \epsilon_{it}.$$
(2)

 exp_{it} is now experience on the labor market, accounting for when individual *i* left school and possible periods of unemployment. X_{it} is the same vector of covariates as in (1). The two other differences with the estimation of (1) are that wages are only observed at the time of hire (the EG panel is unbalanced), and individuals are last surveyed in their eight years after leaving school. Table 1 presents the results from estimating equation (2) on the EG panel. The estimation confirms the observation from Figure 1: average starting wages increased over time for all education levels, but returns to experience decreased between the 1998 and 2010 HEGs¹¹. Further decomposition by gender in Appendix B shows both men and women are experiencing a drop in returns to experience, but the drop is more pronounced for men.

	log entry wage		
Cohort	1998	2004	2010
non-HEG	6.97***	7.06***	7.07***
	(.003)	(.004)	(.005)
HEG	7.25***	7.26***	7.33***
	(.004)	(.004)	(.005)
non-HEG \times Exp.	.040***	.035***	.040***
	(.001)	(.001)	(.002)
HEG \times Exp.	.058***	.047***	.042***
	(.001)	(.002)	(.002)
FE gender, urban, part-time	\checkmark	\checkmark	\checkmark
Observations	43,398	32,348	21,178
R ²	.333	.384	.400

Table 1: Wage profiles by education level - EG panel

Notes: Source: EG panel. Author's own calculations from OLS estimation of equation (2): $\log w_{it} = \sum_{e \in \{l, h\}} \mathbb{1}_{[e_i=e]} (\alpha^{ce} + \beta^{ce} exp_{it}) + \gamma^c X_{it} + \epsilon_{it}$. by cohort. *p<0.1; **p<0.05; ***p<0.01.

Both the EE cross-section and EG panel point to the same changes in returns to experience in France in the last 30 years: average starting wages rose for all education levels, but wage progression slowed down for young higher education graduates. Explaining these two observations together is not straightforward: the canonical supply and demand model predicts a flat decrease in young educated workers' wages if an education expansion occurs. Th next subsection outlines two other empirical facts, namely the evolution

 $^{^{11}{\}rm The}$ increase in returns to potential experience observed between birth cohorts 1985 and 1988 in Figure 1 cannot be reflected in Table 1, since the 2010 higher education graduates' average birth year is 1985.

of occupational sorting and wage profiles by occupation, that will help understand the mechanisms behind the flattening wage progression of higher education graduates.

2.3 Wage Profiles by Occupation

The occupational congestion argument developed in the next section rests on the analysis of wage profiles by occupation. The French occupational classification at the 1-digit level splits into seven categories: 1. Farmers, 2. Artisans and shopkeepers, 3. The military, 4. Factory workers, 5. Employees, 6. Intermediary Professionals, 7. Highly qualified professionals¹². 94.3% of the active population in the EE cross section is employed in the four latter occupations, on which the analysis focuses. Long HEGs (4-year degrees or more)are predominantly employed as Highly qualified professionals, but sorting changes over the 1970 to 1988 cohorts among long HEGs. In the 1970 cohort, 53% of long HEGs are employed as highly qualified professionals. In the 1988 cohort 45% are, a 8 percentage point decrease. Meanwhile, the share of intermediary professionals among long HEGs increases between these two cohorts from 33% to 41%. Short and non-HEGs' sorting is more stable than long HEGs' over this period, except for a decrease in the share of factory workers and a rise in the share of employees among non-HEGs. Figure 10 in Appendix B details this evolution. These observations are also made in the US by the recent literature on the declining returns to skills, for instance in Beaudry et al. (2015).

In parallel to the changes in occupational sorting, wage profiles within occupations also vary between the 1970 and 1988 cohorts. Since the most significant change in sorting among long HEGs occurs between highly qualified and intermediary professionals, I split occupations into two categories for the remainder of the analysis: complex (includes highly qualified professionals) and routine (includes intermediary professionals, employees, and factory workers). One can run a similar regression to (1) by cohort to quantify wage profiles by occupation:

$$\log w_{it} = \sum_{o \in \{r, c\}} \mathbb{1}_{[o_i = o]} \left(\alpha^{co} + \beta^{co} potexp_{it} \right) + \gamma^c X_{it} + \epsilon_{it}.$$
(3)

where o is the complex or routine occupation. The estimated coefficients are plotted in Figure 2. On the left pane, the initial average wage in complex occupations is signifi-

 $^{^{12}}$ Appendix B contains examples of jobs belonging to this categories.

cantly higher than in routine occupations for all cohorts. On the right pane, returns to experience are also higher overall in complex occupations than in routine ones. However, this difference is not significant for the 1976 to 1984 birth cohorts. There are two main takeaways from this graph. First, the initial average wage significantly increased across cohorts in the routine occupation. Second, returns to experience significantly rise between the 1970 and 1980 cohorts in routine occupations, while the returns in the complex occupation fall.



Figure 2: Wage Profiles by Occupation



Notes: Source: EE cross-section. Author's own calculations from OLS estimation of equation (1): $\log w_{it} = \sum_{e \in \{l, h\}} \mathbb{1}_{[e_i=e]} (\alpha^{ce} + \beta^{ce} potexp_{it}) + \gamma^c X_{it} + \epsilon_{it}$. by cohort. For comparison with the EG panel, the vertical dotted lines refer to the average birth year of the 1998, 2004, and 2010 EG cohorts, with and without a higher education degree.

The empirical facts described in this section suggest that HEGs' flattening wage progression stems from the declining returns to experience in complex occupations. The object of the following section is to build and estimate a life-cycle model of capital accumulation with occupational sorting, which accounts for all the empirical facts described in this section and is able to explain HEGs' flattening returns to experience through occupational congestion.

3 A Model of Occupational Sorting and On the Job Learning

3.1 Motivation

The previous section evidences three empirical facts: one, the share of HEGs in the French labor market booms between 1990 and 2020. Second, cohorts born in the 1980s enjoy higher average initial wages than their predecessor, but HEGs' returns to experience fall. Third, wage profiles in different occupations are not the same. They improve in the routine occupations for cohorts born in the 1980s (with higher initial wages and returns to experience), but they worsen in the complex occupations. Together, these three facts suggest that human capital accumulation over the early career changed. Indeed, the literature links human capital and wages through education and on-the-job learning (Ben-Porath (1967), Mincer (1974), Heckman et al. (2006a)), meaning that the changes in human capital production over the life-cycle are well-suited to explain the flattening returns to experience. If human capital production slows down, so does wage progression. So why would human capital production slow down? In the context of an education expansion, the human capital held by young graduates when they leave school decreases either because the quality of teaching suffers from the influx of students or because the bar to enter higher education lowers. However, this explanation alone is at odds with the rising starting wages evidenced for HEGs. The supply and demand equilibrium offers an additional layer of explanation: if workers sort into occupations that afford different human capital accumulation speeds, then a change in sorting results in a change in human capital levels a few years after labor market entry. Changes in sorting could result from shifts in workers' underlying ability or changes in the firm production function. In particular, an education expansion would shift the distribution of underlying ability to the right, which alters sorting and produces occupational congestion, whereby a smaller share of educated workers sort into occupations that afford steep capital accumulation.

To formalize these ideas, I develop a model of human capital acquisition through learning-by-doing (Rosen (1972), Blandin (2018)), in which workers accumulate human capital over their life-cycle. Workers enter the labor market with an idiosyncratic level of human capital that depends on their education level. Workers accumulate human capital on the job, which drives wage growth over the life cycle. When entering the labor market, workers must choose what occupation to sort into. Occupations differ in their wage but also in their human capital production function. The model is embedded in a supply and demand framework (Katz and Murphy (1992), Card and Lemieux (2001)). It brings together the dynamics from life-cycle choices and the supply and demand equilibrium. This modeling approach is similar to Deming (2023)'s, which explains the faster growth of educated workers' wages by putting together the same two modeling blocks¹³. I take the model a step further by estimating it on observed moments in the data. In doing so, I am able to measure the impact of changes in educational distribution, firm demand, and human capital accumulation determinants on occupational sorting and wage trajectories.

3.2 Set Up

There are infinitely many workers indexed by *i*. Their mass is normalized to 1. A worker's education level is denoted by e = HEG if they are higher education graduates, and e = nHEG otherwise. They go through three ages in the labor market: young (a = 1), middle-aged (a = 2), and senior (a = 3). At a = 4, workers retire and get a pension that is the same for all *i*. Worker *i* enters the labor market at a = 1 endowed with an initial level of human capital h_i and a taste for learning, or learning ability α_i (Rosen (1972), Huggett et al. (2006)). The former is a worker's baseline human capital level, while the latter boosts or hinders human capital production as workers age. Both are individual-specific. Together, (h_i, α_i) will be referred to as the worker's underlying ability. It is akin to the concept of skills developed by Cunha and Heckman (2007) but is treated as exogenous by the model, which is agnostic as to its origin (innate or acquired). There is an exogenous share *s* of higher education graduates that enters the labor market¹⁴. A worker's degree changes the distribution from which (h_i, α_i) are drawn. Let ϕ_{nHEG} (resp. ϕ_{HEG}) be the distribution of h_i for non-higher education graduates (resp. higher

¹³Deming (2023)'s model of human capital acquisition is based on the Ben-Porath (1967) model, in which workers choose between labor and learning, which the present model does not feature.

¹⁴In the case of France, the education expansion of the 1990s and 2000s was enabled by a large institutional push that created new higher education degrees and opened new higher education institutions (Dupray and Moullet (2010), Verdugo (2014), Elio (2023)). Public higher education is virtually free, and the state subsidizes time spent studying for students from low-income families. I therefore argue that the choice to pursue a higher education degree in France depends on high school grades, spatial proximity, public subsidies, and parents' socio-economic background rather than on income maximization in the long-term.

education graduates). Both distributions are assumed to be bivariate log-normal. We expect ϕ_{HEG} to be shifted right compared to ϕ_{nHEG} as higher education graduates should have overall higher initial human capital, but make no assumption. Workers choose to work in one of two occupations $o \in \{r, c\}$. r refers to the routine occupation, c to the complex occupation. Occupations differ by the wage they pay per unit of capital, w_o , and by their human capital production function. Human capital in any occupation at age 1 is equal to h_i . At age a > 1, if worker i is employed in occupation o, then their human capital level evolves according to a Cobb-Douglas production function:

$$h_{o,1} = h_i \text{ and } h_{o,a+1} = K_o \alpha_i^{\theta_o} h_{o,a}^{\delta_{eo}}$$

$$\tag{4}$$

where $K_o > 0$. When employed in occupation o, worker i's human capital level at a + 1 depends positively on their human capital at $a h_{o,a}$, and their taste for learning α_i . The latter can also be interpreted as a time investment in learning, in the spirit of a Ben-Porath (1967) model of human capital acquisition. The difference is that time investment is exogenized here, whereas it is a worker's decision in a Ben-Porath model. This simplification allows the present model to focus on the worker's choice of occupation while accounting for heterogeneity in workers' investment in human capital production. The model remains agnostic as to the source of the heterogeneity (taste or ability). In Equation (4), K_o is an occupation-specific output multiplier, while θ_o and δ_{eo} are the taste for learning's and human capital's output elasticities. K_o , θ_o and δ_{eo} all depend on occupation o. The parameter δ_{eo} also depends on education level e^{15} . δ_{eo} would absorb any human capital depreciation from age a to a + 1,

Equation (4) implies that human capital at age a > 1 is occupation-specific. A direct implication of this assumption is the absence of occupational mobility between complex and routine occupations. Table 12 in Appendix B reports mobility patterns for the EG panel and shows a small minority of individuals switch occupations (14.2 % of higher education graduates and 2.8% of non-higher education graduates).

Workers maximize their cumulative log earnings by choosing the occupation o they

¹⁵This allows depreciation to vary depending on the type of human capital acquired at school.

work in. At every age a, worker i earns $w_o h_{ao}$. The worker's problem is

$$\max_{o \in \{r,c\}} LE_o(h_i, \alpha_i) = \sum_{a=1}^3 \beta^{a-1} \log(w_o h_{o,a})$$

s.t $\log h_{o,a+1} = \log A_o + \theta_o \log \alpha_i + \delta_{eo} \log h_{o,a}$
 $\log h_{o,1} = \log h_i$ (5)

Given wages $w = (w_r, w_c)$, workers choose $o \in \{r, c\}$ to maximize their life-time cumulative earnings. Aggregating workers' choices over all ages results in R^s and C^s , the aggregate human capital supplied to occupations r and c.

On the demand side, there is a unique representative firm producing a single good Y. Its production is modeled by a Constant Elasticity of Substitution (CES) function:

$$Y(R,C) = (A_r R^{\tau} + A_c C^{\tau})^{\frac{1}{\tau}}$$
(6)

The parameters (A_r, A_c) measure the productivity of each occupation, and τ the substituability between r and c. The quantities R and C are the total amounts of human capital demanded by the firm, given wages w.

Firms maximize profits by hiring $(\mathbb{R}^d, \mathbb{C}^d)$

$$Y(R^d, C^d) - w_r R^d - w_c C^d.$$

At optimum, efficiency wages are equal to marginal productivity:

$$w_r = \frac{\partial Y(R^d, C^d)}{\partial R} \text{ and } w_c = \frac{\partial Y(R^d, C^d)}{\partial C}$$
 (7)

The equilibrium in this model is a tuple of wages and human capital (w_r, w_c, R, C) such that the labor demanded by the firm in each occupation is equal to the labor supplied by workers:

$$R = R^d = R^s$$
 and $C = C^d = C^s$.

The equilibrium exists and is unique. Appendix C provides a proof of this result.

3.3 Model Mechanisms

Given wages (w_r, w_c) , young workers choose their occupation by comparing life-cycle earnings in r and c. Intuitively, if we expect occupation c to provide better human capital accumulation than r for all workers (i.e., if $A_c > A_r$, $\theta_c > \theta_r$ and $\delta_c > \delta_r$), then it cannot be that unit wage w_c is more than w_r . If this were the case, all workers would strictly prefer the complex occupation. This situation is suboptimal for the firm, which also needs workers to be employed in the routine occupation as long as $A_r > 0$. So at equilibrium $w_c < w_r$. We therefore expect a steep human capital accumulation in occupation c to bear negatively on $\frac{w_c}{w_r}$, and vice-versa. The magnitude of this effect depends on the relative productivity $\frac{A_c}{A_r}$: if it is tiny, the effect is almost absent. Depending on the human capital production parameters, however, the comparison of human capital production between cand r may not be as clear-cut: it could be that $\theta_c < \theta_r$ if the time investment matters less in c than in r, or that $\delta_c < \delta_r$ if there is more human capital depreciation in c than in r. In this case, c would yield steeper human capital accumulation for some workers but not others, depending on their underlying ability (h, α) . Understanding the workers' decision, therefore, requires a closer inspection of their lifetime earning maximization problem (5).

To choose their occupation upon labor market entry, workers compute the difference in lifetime earnings between occupation c and r:

$$\Delta LE(h, \alpha, w) = LE_c(h, \alpha, w_c) - LE_r(h, \alpha, w_r)$$

and choose c if $\Delta LE(h, \alpha, w) > 0$ and r otherwise. This behavior results in contour function $h \to \alpha^*(h, w)$ such that a worker endowed with underlying ability (h, α) sorts into c if $\alpha > \alpha^*(h, w)$ and r otherwise, under some assumptions on $\delta_r, \delta_c, \theta_r$ and θ_c . More details on sorting are provided in Appendix C.

If c is the highest human capital returns occupation, workers who sort in c are paid a relatively smaller wage at age a = 1 than they would be paid in r, but as they accumulate more human capital at age a = 2, 3, their wage increases faster. When an education expansion occurs, the share of higher education graduates in the working population s increases, and more workers draw their underlying ability from ϕ_{HEG} . Assume that ϕ_{HEG} is shifted to the right compared to ϕ_{nHEG} meaning HEGs generally have a higher initial human capital and taste for learning. Then, the education expansion increases overall initial human capital and ability to learn, and a greater mass of workers are above the $(h, \alpha^*(h))$ contour curve and sort into the complex occupation. However, the firm still needs workers to sort into the routine occupation, so in this new equilibrium, $\frac{w_c}{w_r}$ is lower than in the previous one. As a consequence, a smaller fraction of higher education graduates sort into the complex occupation, a phenomenon this paper refers to as occupational congestion. These workers start with higher wages than they would have without the education expansion, thanks to a high unit wage w_r . However, they also acquire less human capital over their life-cycle, which flattens their wage progression. This mechanism is related to the literature on over-education (Chevalier (2003), Dolton and Silles (2008)), which studies high-skill workers who sort into jobs with low skills requirements (the 'over-educated'). In the present model, there is no assumption of what skills the routine and complex occupations require; the only difference between the two rests on the human capital production parameters.

The model is, therefore, consistent with the empirical facts observed in the data. The effects of an education expansion described above do not preclude other changes, such as shifts in the distributions of initial human capital or technological change in the firm production function. In the next section, I estimate the model on the EE cross-section to distinguish the contribution of these different factors.

4 Estimation and Counterfactuals

The model mechanisms described in the previous section are qualitatively consistent with the empirical facts described in section 2. This section aims to measure how each of these contributes to changes in the wage profiles. It estimates the model on the EE cross-section and uses the estimates to run counterfactuals.

4.1 Strategy

I estimate the model with a method of moments to measure how education expansion, technological change, or changes in human capital accumulation contribute to changes in wage profiles.

The model is parametrized as follows: initial human capital distributions $(\phi_e)_e$ are

log-normal, where. The distribution parameters are $((\mu_e, \Sigma_e))_{e \in \{n \in \{n \in G, H \in G\}}$, with

$$\mu_e = \left(\mu_e^h, \mu_e^\alpha\right), \ \Sigma_e = \begin{bmatrix} \sigma_e^h & \rho_e \\ \rho_e & \sigma_e^\alpha \end{bmatrix}.$$

 μ_e^h and μ_e^{α} are the location parameters for random variables h and α , and σ_e^h and σ_e^{α} are the scale parameters. The correlation parameter between initial human capital h and taste for learning α is ρ_e^{16} .

There are three age bins (1: young -less than 30 years old- 2: middle-aged -from 31 to 45- 3: senior -more than 46-). This bin structure aims to capture the initial wages at the start of the career. As before, the complex occupation refers to 'highly qualified professionals', and the routine occupation refers to 'intermediary professionals', 'employees', and 'factory workers.' In total, there are 21 parameters in the model:

$$\Gamma = \left(\underbrace{A_r, A_c, \tau}_{\text{Firm production}}, \underbrace{K_r, K_c, \theta_r, \theta_c, \delta_{0r}, \delta_{1r}, \delta_{0c}, \delta_{1c}}_{\text{Human capital production}}, \underbrace{\mu_0^h, \mu_0^\alpha, \mu_1^h, \mu_1^\alpha, \sigma_0^h, \sigma_0^\alpha, \rho_0, \sigma_1^h, \sigma_1^\alpha, \rho_1}_{(h, \alpha) \text{ distribution}}\right)$$

The estimation uses the first and second moment of the log wage distribution by education level, age bin, and occupation, as well as the share of non-HEGs and HEGs who sort into each occupation. The observed moments are therefore:

$$\left(\widehat{\log w}_{eao}, \widehat{\log w^2}_{eao}, \widehat{s}_{eo}\right)_{e \in \{\text{nHEG}, \text{ HEG}\}, a \in \{1, 2, 3\}, o \in \{r, c\}}$$

The model counterparts to the data moments are

$$\left(\overline{\log w}_{eao}(\Gamma), \overline{\log w^2}_{eao}(\Gamma), s_{eo}(\Gamma)\right)_{e \in \{\text{nHEG}, \text{ HEG}\}, a \in \{1,2,3\}, o \in \{r,c\}}$$

Appendix D details the explicit expressions for these moments. The discount factor β is fixed to .95. The substitution parameter τ is calibrated to .31, based on Patel (2020), which estimates the elasticity of substitution between the complex and routine occupations to be 1.45¹⁷. The model is invariant to the productivity parameters $(A_r, A_c)^{18}$, so

¹⁶Since ϕ_e is log-normal, μ_e and Σ_e are also the vector of expected values and the variance-covariance matrix of random variables (log h, log α)

 $^{^{17}}$ Patel (2020) 's model also includes manual occupations, which substitute to routine and complex with elasticity 2.76. In the present model, routine and manual are bundled.

 $^{^{18}\}mathrm{This}$ is because of the homogeneity of the CES production function

 A_r is fixed to 1. The last set of parameters that is calibrated is $(\delta_{e,o})_{e,o}$. Simple algebra on the model's equation shows that:

$$\delta_{eo} = \frac{\overline{\log w}_{3eo}(\Gamma) - \overline{\log w}_{2eo}(\Gamma)}{\overline{\log w}_{2eo}(\Gamma) - \overline{\log w}_{1eo}(\Gamma)}$$

Each δ_{eo} is calibrated by replacing the model's moments with the data moments computed over all years 1991 to 2020 in the EE cross-section. Calibrated parameters are reported in Table 11. All δ_{eo} are calibrated below 1, indicating that human capital depreciation occurs for every education level and in every occupation. However, it does not occur at the same rate for all education levels and occupations. The depreciation rate is higher in the routine occupation for both education levels, suggesting either that routine human capital is more specialized than complex or that complex work allows workers to build on previous knowledge more than routine. The depreciation rate is also lower for HEGs in both occupations, which shows that HEGs' human capital is more general and robust and used in a broader range of tasks.

Parameter	Value
eta	.95
au	.31
A_r	1.
$[\delta_{0,r}\delta_{1,r}\delta_{0,c}\delta_{1,c}]$	[.87 .94 .93 .94]

 Table 2: Calibrated parameters

Source: Patel (2020), EE cross-section. Author's own calculations

In total, there are 12 wage first moments, 12 wage second moments, and 2 sorting shares that identify the 15 remaining parameters in Γ . The model separately over ten periods of three years: 1991-1993, 1994-1996, 1997-1999, 2000-2002, 2003-2005, 2006-2008, 2009-2011, 2012-2014, 2015-2017, 2018-2020. In each period, empirical moments are computed over all three years to ensure outlier years are smoothed out, and also provide enough estimation points to discern how the parameters change over time.

4.2 Results

Two predicted moments sum up the model's fit after estimation: sorting into the complex occupation and average wage growth between age 1 and 3 in each occupation, both by education level and time period. In the remainder of the analysis, they are referred to as $s_{eo}^{\text{pred}} = s_{eo}(\hat{\Gamma})$ and $\log w_{aeo}^{\text{pred}} = \log w(\hat{\Gamma})_{aeo}^{19}$. Table 3 presents descriptive statistics on the difference between data and predicted moments. On average, the model fits exactly (to 3 decimals) both the sorting shares and wage progression. The maximum difference in sorting is .008 (out of a sorting share of .592), and the largest difference in wage progression is .062 (out of a 1.177 predicted wage progression). The model is therefore a good fit for the data and is able to reproduce the changes in sorting and wage progression over time.

	$\hat{s}_{eo} - s_{eo}^{\text{pred}}$	$\frac{\widehat{\log w_{3eo}}}{\widehat{\log w_{1eo}}} - \frac{\log w_{3eo}^{\mathrm{pred}}}{\log w_{1eo}^{\mathrm{pred}}}$
Mean	.000	.000
Min	008	019
Max	.008	.062

Table 3: Predicted versus observed moments

Notes: Source: EE cross-section. Author's own calculations. The time subscript is omitted.

Given that the model is able to reproduce overall changes in sorting and wage progression, the estimated parameters are informative on the role played by supply and demand changes in the flattening wage growth. Figure 3 shows the changes in initial human capital h and learning ability or taste for learning α 's location parameter for both education groups over time, $(\mu_{nHEG}^{h}, \mu_{nHEG}^{\alpha}, \mu_{HEG}^{h}, \mu_{HEG}^{\alpha})$. These parameters are roughly constant over time, with a slight downward trend for μ_{nHEG}^{h} and μ_{HEG}^{h} , which indicates average initial human capital goes down over time. Note that μ_{nHEG}^{α} is below zero, suggesting that taste for learning is a liability in human capital accumulation for non-HEGs. HEG's location parameters are always higher than non-HEGs. This finding is consistent both with a theory of selection, whereby individuals with higher human capital and learning ability enter higher education, and a theory of learning, whereby individuals improve their human capital and ability to learn while in higher education. The downward trend

 $^{^{19}\}mathrm{Time}$ subscript are omitted

on μ_{nHEG}^{h} and μ_{HEG}^{h} could be caused by worsening education quality or milder selection into higher education. Both μ_{nHEG}^{α} and μ_{HEG}^{α} remain constant over the period however, which suggests that learning ability is not affected by the education expansion.

Figure 3: Estimated $(\log h, \log \alpha)$'s expected values



Notes: Source: EE cross-section. Author's own calculations. Standard errors are computed with 50 bootstraps.

Figure 4 reports the estimated scale parameters for distribution (h, α) . On the left pane, Non-HEGs display a lower variance for initial human capital log h than HEGs, but the opposite is true of learning ability log α . Non-HEGs' scale parameters both decrease over the period, while HEGs' scale parameter for h increases. This finding is consistent with a theory selection into higher education based on ability. If the bar to enter higher education is lowered over time, we should expect variance in ability amongst HEGs (resp. non-HEGs) to increase (resp. decrease). However, this could also be due to the development of new higher education institutions, which increase the heterogeneity in education quality. On the right pane, the correlation between initial human capital and learning ability is positive for both education levels and varies little over the period. They are not significantly different after 2000-2002.



Figure 4: Estimated $(\log h, \log \alpha)$'s variance and covariance

Notes: Source: EE cross-section. Author's own calculations. Standard errors are computed with 50 bootstraps.

Figure 5 shows the estimated productivity parameter for the complex occupation A_c . The complex occupation is estimated to be less productive than the routine occupation. Indeed, in the data, more workers sort into the routine than the complex occupation, which the model can only rationalize if the total human capital provided in the routine occupation is larger than in the complex. This translates to $A_r > A_c$, given the CES assumption. A_c is rising over time compared to A_r , in line with the findings from the literature on skill-biased technological change (Goldin and Katz (2008)).



Figure 5: Estimated productivity parameters - A_o

Notes: Source: EE cross-section. Author's own calculations. Standard errors are computed with 50 bootstraps.

Finally, Figure 6 shows the estimated occupation-specific gains to human capital K_o and returns to learning ability θ_o . The occupation-specific human capital production K_o is higher in the routine than in the complex occupation. It also decreases slightly over time in the routine occupation. Return to learning ability θ_o is higher in the complex than in the routine occupation and is roughly constant over time in both occupations. θ_r is even slightly below zero, suggesting learning ability is more a hindrance than a help to human capital production in the routine occupation. In comparison, it is highly rewarded $(\theta_c > 1)$ in the complex occupation.



Figure 6: Estimated occupation specific learning parameters - K_o , θ_o

Notes: Source: EE cross-section. Author's own calculations. Standard errors are computed with 50 bootstraps.

The estimated parameters point to two main changes in the French labor market over the period: first, the distribution of workers' underlying ability shifts slightly: average initial human capital declined, and its variance rises for HEGs and lowers for non-HEGs. These changes are modest but could still impact starting wage and wage progression. Second, productivity in the complex occupation grows, which boosts wages in that occupation. Human capital production stays mostly the same over the period.

4.3 Counterfactuals

To isolate the impact of each model parameter on the wage profile changes discussed in section 2, I conduct four counterfactual analyses. In each one, the model equilibrium is computed for one set of fixed parameters, while the others are allowed to vary as estimated. The counterfactual moments are then compared to the predicted moments. The outcomes I focus on are sorting into the complex occupation, average wage at ages 1 and 3, and wage progression, all by education level. Let $w_{e,a}^{pred}$ be the average wage predicted by the model in age a and at education level e:

$$\log w_{e,a}^{\text{pred}} = \sum_{o \in \{r,c\}} s_{eo}^{\text{pred}} \times \log w_{aeo}^{\text{pred}}$$

then wage progression in education level e is $\frac{\log w_{3e}^{\text{pred}}}{\log w_{1e}^{\text{pred}}}$.

Table 4 shows the sorting and wage moments as predicted by the model. These predictions confirm the drop in return to experience already highlighted in Section 2: senior HEGs' log wage is 33% higher than young HEGs' in 2000-2002, but only 25% higher in 2018-2020. Senior HEGs' wages are driving this decrease. Non-HEGs experience the same trend (from 29% to 21%). Note that these two observations differ in their angle from the empirical facts established in Section 2: regressions (1) and (2) measure the change in wage progression across cohorts. In contrast, the model measures it across time. Both measures are consistent: the progressive flattening of returns to experience results in a decrease in final wage across cohorts. This consistency shows in the model's prediction through a fall in $\log w_{3e}^{\text{pred}}$ over time: from 2.78 to 2.74 for HEGs between 1991-1993 and 2018-2020. Sorting in the complex occupation also declines among HEGs, from .43 to .4 over the same period. Table 4 displays the same bell-shaped trend for HEG's wage progression as Figure 1: it rises between 1991-1993 and 200-2002, peaks, and then falls throughout the rest of the period. Non-HEGs wage progression displays a similar pattern, although the final wage does not decrease as much as for HEGs.

	$s_{ec}^{\rm pred}$	$\log w_{1e}^{\rm pred}$	$\log w_{3e}^{\rm pred}$	$\frac{\log w_{3e}^{\rm pred}}{\log w_{1e}^{\rm pred}}$
non-HEG				
1991-1993	0.05	2.1	2.36	0.25
2000-2002	0.04	2.07	2.36	0.29
2009-2011	0.06	2.15	2.38	0.23
2018-2020	0.04	2.15	2.36	0.21
HEG				
1991-1993	0.43	2.51	2.78	0.27
2000-2002	0.41	2.45	2.78	0.33
2009-2011	0.4	2.47	2.76	0.29
2018-2020	0.4	2.49	2.74	0.25

 Table 4: Predicted sorting and wages

Notes: Source: EE cross-section. Author's own calculations.

Each counterfactual keeps one set of primitives or parameters fixed at its 1991-1993

level while allowing the other parameters to vary as estimated. Counterfactual 1 maintains a constant share of HEG s in the worker's population. Counterfactual 2 fixes the underlying ability distribution $(h, \alpha)^{20}$. Counterfactual 3 cancels skill-biased technological change by keeping A_c constant. Finally, Counterfactual 4 fixes the parameters of human capital production K_o and θ_o .

Let $\Delta m = m^{\text{pred}} - m^{\text{count}}$ be the difference in moment m between the model prediction and the counterfactual. Table 5 shows the difference in predicted and counterfactual moments for HEGs in 2009-2011 and 2018-2020, and Table 6 shows the same difference for non-HEGs. Two primary groups of counterfactuals emerge: those leading to greater-than-predicted wage growth (counterfactuals 1 and 4: fixing the share of HEGs in the worker population and the human capital production parameters), and those that result in a lower wage progression (counterfactual 2: freezing the underlying ability distribution). Canceling technological change does not affect wage progression. In the first group, both counterfactuals steepen wage growth, albeit via different mechanisms. Counterfactual 1, Fixing the share of HEGs produces higher sorting of HEGs in the complex occupation ($\Delta s_{\text{HEG},c} < 0$), raising final wages significantly in both periods ($\Delta w_{3\text{HEG}} < 0$) due to faster human capital accumulation in complex occupation. In contrast, fixing human capital production parameters does not alter occupational sorting but slightly accelerates human capital production, leading to a modest increase in HEGs' final wage. The effect of locking in the share of HEGs is more potent in 2018-2020 than freezing the human capital production parameters: wage growth is 3 percentage points higher in the former but only 1 percentage point higher in the latter. In the second group, freezing the distribution of (h, α) boosts initial wages, primarily by raising the average initial human capital ($\Delta w_{1\text{HEG}} < 0$). This effect persists, albeit diminished, for final wages, resulting in reduced overall wage progression relative to the model prediction. Appendix E includes an additional counterfactual analysis where both the HEG share and the distribution of underlying ability are fixed (a merge of counterfactuals 1 and 2). This pairing is theoretically linked: the education expansion could shift the underlying ability distribution leftward, reflecting a potential decline in education quality or reduced selection. The combined counterfactual shows higher HEG sorting in the complex occupation, similar to counterfactual 1, where the HEG share is frozen, and slower wage growth, similar to

²⁰Appendix E runs counterfactual 5, which freezes both the share of HEGs over time and the distribution of (h, α) .

counterfactual 2, with only the underlying ability distribution fixed. The impact of fixing the underlying ability distribution on wage growth dominates over fixing the HEG share. Finally, Cancelling technological change has the opposite effect: it decreases both initial and final wages, mainly because fewer HEGs sort into the complex occupation since it is less productive ($\Delta s_{e,c} > 0$). Overall, the observations from Table 5 imply that the education expansion is primarily responsible for the slowdown in wage growth: had it not happened, wage growth would have been steeper. Changes in the underlying ability distribution have a substantial but opposite effect, depressing wage growth. The effect of the changes in underlying distribution still occurs when coupled with the education expansion.

	Δs_{eo}	$\Delta \log w_{e1}$	$\Delta \log w_{e3}$	$\Delta \frac{\log w_{e3}}{\log w_{e1}}$
2009-2011				
1. % HEG	-0.19	-0.01	-0.01	0.0
2. (h, α) distrib	-0.01	-0.19	-0.15	0.02
3. Tech. change	0.15	0.15	0.16	-0.0
4. HC prod.	-0.0	-0.0	-0.01	-0.01
2018-2020				
1. % HEG	-0.5	0.01	-0.06	-0.03
2. (h, α) distrib	0.05	-0.2	-0.18	0.01
3. Tech. change	0.16	0.18	0.2	0.0
4. HC prod.	0.0	-0.01	-0.03	-0.01

 Table 5: Counterfactual sorting and wage - HEGs

Notes: Source: EE cross-section. Author's own calculations.

Table 6 shows the same counterfactuals for non-HEGs (e = 0). The results are similar to those of HEGs, but the magnitudes of the changes in initial and final log wages are smaller than those of HEGs. The share of non-HEGs sorting into the complex occupation is lower than HEGs, which is reflected in more minor changes in Δs_{ec} .

	Δs_{ec}	$\Delta \log w_{e1}$	$\Delta \log w_{e3}$	$\Delta \frac{\log w_{e3}}{\log w_{e1}}$
2009-2011				
1. % HEG	-0.01	0.0	0.0	-0.0
2. (h, α) distrib	0.01	-0.1	-0.09	0.01
3. Tech. change	0.01	0.14	0.14	-0.01
4. HC prod.	0.0	0.0	-0.03	-0.01
2018-2020				
1. % HEG	-0.0	0.0	0.0	-0.0
2. (h, α) distrib	-0.01	-0.15	-0.14	0.01
3. Tech. change	0.0	0.18	0.18	-0.01
4. HC prod.	0.0	0.01	-0.04	-0.02

Table 6: Counterfactual sorting and wage - Non-HEGs

Notes: Source: EE cross-section. Author's own calculations.

The counterfactuals show that the supply side is responsible for the biggest changes in wage progression, i.e., the education expansion and changing distribution of underlying ability. These two drivers have substantial and opposite effects: the former depresses wage growth through lower sorting in the complex occupation, while the latter boosts wage progression, but mostly because it depresses initial wages. On the demand side, technological change boosts wage levels in the complex occupation but does not impact wage progression much. Changes in the human capital production function, although small, have a negative impact on wage progression. The counterfactual analysis therefore shows that the education expansion is mainly causing the flattening returns to experience, while changes in the underlying ability distribution are mostly depressing initial wages. This effect is partly compensated by technological change, which boosts wage levels at all ages in the complex occupation.

5 Conclusion

This paper examines shifts in wage trajectories for workers born between 1970 and 1986 in France. It shows that while wages at labor market entry increased for all workers, the wage growth, or returns to experience, of higher education graduates (HEGs) has flattened. Concurrently, the share of HEGs in the workforce rose, but the proportion of HEGs employed in complex occupations declined. To explain these patterns, the paper develops a life-cycle model of human capital accumulation, incorporating differential human capital production by occupation and a demand side represented by a representative firm. The model successfully replicates the observed patterns in the French labor market. Its key mechanism in an education expansion is occupational congestion: when educational attainment rises in the worker population, the baseline wage in routine occupations rises relative to complex occupations. The change in relative wages leads a larger share of HEGs to enter routine occupations, where returns to human capital are lower than in complex roles. In the routine occupation, workers benefit from higher starting wages, but lower wages in the middle and end of their career. The paper estimates the model on the data's wage and sorting moments. The estimation points to worsening education quality, lowering selection in education, and skill-biased technological change. The paper runs counterfactuals based on the estimates obtained and finds that the education expansion (i.e., the increase in the share of higher education graduates on the labor market) is the primary driver of the flattening wage progression. At the same time, the changes in the distribution of underlying ability have a steepening effect on wage growth.

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A Data Cleaning

I use two datasets to evidence the flattening returns of experience and explore its mechanisms: the first is the EE cross-section, *Enquêtes Emplois*, produced by INSEE, the French Institute for Statistics and Economic Studies, and the second is the EG panel, *Enquêtes Générations*, a survey conducted by CEREQ, the Centre for Study and Research on Qualifications.

The EE cross-section is a yearly national labor force survey that has run since 1950. In this paper, I use the years 1990 to 2020²¹. It surveys a representative sample of French residents between the ages of 15 and 89. The main variables I use from this survey are individual age, education level, employment status, wage, and occupation. The sample used for the analysis covers active workers who are at least 20 years old if they are non-HEG, and 24 years old if they are HEG. I exclude all workers at 65 years old or above, and 55 yezrs old or above in the model estimation²². Workers earning less than 600 euros/month and more than 15,000 euros/months, as well as the 1st and 99th wage percentiles are excluded. Workers are considered part time if they work less than 37 hours a week. Hourly wage is computed from monthly wage and hours worked per week. Workers are urban if they live in one of the ten most populous cities in France (Paris, Marseille, Lyon, Toulouse, Nice, Nantes, Montpellier, Strasbourg, Bordeaux, Lille). The weight variable EXTRI is used in the regressions. Potential experience is computed as the difference between actual age and 20 (for non-HEGs) or 24 (for HEGs). Table 8 displays descriptive statistics for these variables over the 1990-2020 period.

% women	45.7
%urban	21.5
% part-time	15.2
Average age	40.2

Source: EE cross-section: all employed individuals 1990-2020. Author's own calculations.

The *Enquêtes Générations* EG panel is a survey that follows a graduation cohort over the first seven years of their professional lives. Every six years, the CEREQ surveys a representative sample of school leavers at different education levels, from high school

²¹Starting in 2003, the survey is run every trimester, but I do not exploit this dimension, and treat the data as a cross-section.

 $^{^{22}\}mathrm{The}$ model is unable to reproduce the dip in wage observed after 55

dropouts to Ph.D. graduates. The surveys used in this paper cover three cohorts, who leave school in 1998, 2004, and 2010. I refer to the cohort who left school and entered the labor market in year X as the X cohort. Each cohort is surveyed for up to eight years after they leave school. As such, the Generation Surveys provide a comprehensive outlook of early career outcomes in the French labor market between the end of the 1990s and the 2010s. The surveys are presented as an unbalanced panel: each observation corresponds to the activity of an individual (employment or unemployment) over a given period, referred to as a spell. Only individuals who responded to all three surveys are included in the analysis. I also exclude spells started when the individual is less than 16 years old (the legal working age in France), employment spells that report starting wages below $200 \in$ or above $20,000 \in$, or employment spells whose starting occupation or industry is unknown.

need to harmonize data cleaning between the two datasets

Tables 7 and 8 show the surveys' size and descriptive statistics on the variables used in the analysis.

Cohort	1998	2004	2010
Number of individuals	13,729	9,700	7,702
Number of spells	73,953	55,218	39,241
Number of employment spells	44,330	34,078	23,798
Average number of spells by ind.	4.8	5.2	5.0
Average number of employment spells by ind.	2.7	2.9	2.7

 Table 7: EG panel - spells and observations

Notes: Source: EG panel. Author's own calculations.

% women	49.7
% urban	25.3
% part-time	15.2
Av. Age at grad - HEG	24.2
Av. Age at grad - non HEG	20.0

 Table 8: EG panel - Descriptive Statistics

Panel: all individuals in graduating cohorts 1998, 2004, 2010

B Empirical Facts



B.1 The French Education Expansion

Figure 7: Share of higher education graduates over time

Notes: Source: EE cross-section.

B.2 Wage Profiles

B.2.1 Varying the estimation window on EE cross-section



Figure 8: Wage profiles by education level - EE cross section



Notes: Source: EE cross-section. Author's own calculations from OLS estimation of equation (1): $\log w_{it} = \sum_{e \in \{l, h\}} \mathbb{1}_{[e_i=e]} (\alpha^{ce} + \beta^{ce} potexp_{it}) + \gamma^c X_{it} + \epsilon_{it}$. by cohort over 15 years. For comparison with the EG panel, the vertical dotted lines refer to the average birth year of the 1998, 2004 and 2010 EG cohorts, with and without a higher education degree.



Figure 9: Wage profiles by education level - EE cross section

📧 Higher Educ. 👱 No Higher Educ.

Notes: Source: EE cross-section. Author's own calculations from OLS estimation of equation (1): $\log w_{it} = \sum_{e \in \{l, h\}} \mathbb{1}_{[e_i=e]} (\alpha^{ce} + \beta^{ce} potexp_{it}) + \gamma^c X_{it} + \epsilon_{it}$. by cohort over 22 years. For comparison with the EG panel, the vertical dotted lines refer to the average birth year of the 1998, 2004 and 2010 EG cohorts, with and without a higher education degree.

B.2.2 Wage profiles by gender - EG panel

Tables 9 and 10 display estimation of equation (2) in the EG panel by gender. Table 9 shows the coefficient for women, 10 for men. Women's average starting wages are lower than mens' across cohorts and education levels. So are their returns to experience. Both male and female HEGs experience a decrease in returns to experience between the 1998 and 2010 cohorts (from 4.6% to 3.6% for women, and from 7.1% to 4.8% for men).

	log	g entry wa	ige
Cohort	1998	2004	2010
non-HEG	6.98***	7.06***	7.07***
	(.004)	(.005)	(.007)
HEG	7.26***	7.26***	7.33***
	(.005)	(.005)	(.007)
non-HEG \times Exp.	.037***	.039***	.040***
	(.002)	(.002)	(.003)
HEG \times Exp.	.046***	.037***	.036***
	(.002)	(.002)	(.003)
FE urban, part-time	\checkmark	\checkmark	\checkmark
Observations	20,970	$16,\!305$	10,334
\mathbb{R}^2	.339	.394	.379

Table 9: Wage profiles by education level - EG panel - Women Notes: Source: EG panel. Author's own calculations from OLS estimation of equation (2): $\log w_{it} = \sum_{e \in \{l,h\}} \mathbb{1}_{[e_i=e]} (\alpha^{ce} + \beta^{ce} exp_{it}) + \gamma^c X_{it} + \epsilon_{it}$. by cohort and gender. *p<0.1; **p<0.05; ***p<0.01.

	log	g entry wa	lge
Cohort	1998	2004	2010
non-HEG	7.08***	7.16***	7.15***
	(.004)	(.004)	(.005)
HEG	7.35***	7.34***	7.40***
	(.004)	(.004)	(.005)
non-HEG \times Exp.	.042***	.032***	.039***
	(.001)	(.002)	(.002)
HEG \times Exp.	.071***	.058***	.048***
	(.002)	(.002)	(.003)
FE urban, part-time	\checkmark	\checkmark	\checkmark
Observations	22,428	16,043	10,844
\mathbb{R}^2	.282	.340	.391

Table 10: Wage profiles by education level - EG panel - Men Notes: Source: EG panel. Author's own calculations from OLS estimation of equation (2): $\log w_{it} = \sum_{e \in \{l, h\}} \mathbb{1}_{[e_i=e]} (\alpha^{ce} + \beta^{ce} exp_{it}) + \gamma^c X_{it} + \epsilon_{it}$. by cohort. *p<0.1; **p<0.05; ***p<0.01.

B.3 Occupational sorting

One-digit Occupation	E.g. Job
Farmers	
Craftmen & Shopkeepers	
Military	
Factory Workers	Unskilled workers
	Skilled workers
	Agricultural worker
	Drivers
Employees	Secretaries
	Policemen
	Sales representative
Intermediary Professionals	School teachers
	Technicians
	Foremen
	Nurses
	Accountants
Highly Qualified Professionals	Engineers
	Executives
	Doctors
	Lawyers
	Professors

 Table 11: Occupation Classification

Notes: From Enquêtes Emplois documentation.



Figure 10: Share of each education level employed by occupation

🖝 Employees 💽 Factory Workers 📼 Highly Qualified Prof. 💽 Intermediary Prof.

Notes: Source: EE cross-section. Author's own calculations on the sample of employed workers with at most 8 years of potential experience. Long HGE hold 4-years degrees or more, short HGE hold 3-years degree or less.

	% Always in Complex	% Always in Routine	% Switch
HEG	25.4	60.4	14.2
Non-HEG	0.1	96.6	2.8

Table 12: EG panel - Occupational Mobility

Notes: Source: EG panel. Author's own calculations.

C Model Equilibrium

Given efficiency wages w, workers compute the difference in cumulative log earnings $\Delta LE(h, \alpha, w) = LE_c(h, \alpha, w_c) - LE_r(h, \alpha, w_r)$ where

$$LE_o(h, \alpha, w_o) = (1 + \beta + \beta^2) \log w_o + \log A_o \left(\beta + \beta^2 (1 + \delta_{eo})\right) + \log \alpha \left(\beta \theta_o + \beta^2 \theta_o (1 + \delta_{eo})\right) + \log h \left(1 + \beta \delta_{eo} + \beta^2 \delta_{eo}^2\right).$$

Setting $\Delta LE(h, \alpha, w) = 0$ yields contour function $h \to \alpha^*(h, w)$ such that $\Delta LE(h, \alpha^*(h), w) = 0$ for all h, where

$$\log \alpha^*(h, w) = -\frac{(1+\beta+\beta^2)\log\frac{w_c}{w_r} + (\log A_c \left(\beta+\beta^2(1+\delta_{ec})\right)) - (\log A_r \left(\beta+\beta^2(1+\delta_{er})\right))}{\theta_c \left(\beta+\beta^2(1+\delta_{ec})\right) - \theta_r \left(\beta+\beta^2(1+\delta_{er})\right)} - \frac{\log h \left(\beta(\delta_{ec}-\delta_{er})+\beta^2(\delta_{ec}^2-\delta_{er}^2)\right)}{\theta_c \left(\beta+\beta^2(1+\delta_{ec})\right) - \theta_r \left(\beta+\beta^2(1+\delta_{er})\right)}.$$

Whether worker *i* chooses occupation *c* when α_i is above or below $\alpha^*(h_i)$ depends on the denominator in the expression above. If

$$\theta_c \left(\beta + \beta^2 (1 + \delta_{ec})\right) - \theta_r \left(\beta + \beta^2 (1 + \delta_{er})\right) > 0$$

then worker *i* endowed with underlying ability (h_i, α_i) such that $\alpha_i > \alpha^*(h_i, w)$ sorts into occupation *c*. Otherwise, worker *i* sorts into occupation *r*. If the denominator is below zero, the opposite is true: workers endowed with $\alpha_i > \alpha^*(h_i, w)$ sort into occupation *r*.

Let us assume without loss of generality that the denominator is positive. The share of workers at age a of education level e that sort into occupation c and r given wages wis

$$L_{1er} = \int_{0}^{\infty} \int_{0}^{\alpha^{*}(h,w)} h\phi_{e}(h,\alpha) d\alpha dh$$

$$L_{1ec} = \int_{0}^{\infty} \int_{\alpha^{*}(h,w)}^{\infty} h\phi_{e}(h,\alpha) d\alpha dh$$

$$L_{2er} = \int_{0}^{\infty} \int_{0}^{\alpha^{*}(h,w)} K_{r} \alpha^{\theta_{r}} h^{\delta_{er}} \phi_{e}(h,\alpha) d\alpha dh$$

$$L_{2ec} = \int_{0}^{\infty} \int_{\alpha^{*}(h,w)}^{\infty} K_{c} \alpha^{\theta_{c}} h^{\delta_{ec}} \phi_{e}(h,\alpha) d\alpha dh$$

$$L_{3er} = \int_{0}^{\infty} \int_{0}^{\alpha^{*}(h,w)} K_{r}^{\delta_{er}} \alpha^{\theta_{r}(1+\delta_{er})} h^{\delta_{er}^{2}} \phi_{e}(h,\alpha) d\alpha dh$$

$$L_{3ec} = \int_{0}^{\infty} \int_{\alpha^{*}(h,w)}^{\infty} K_{c}^{\delta_{ec}} \alpha^{\theta_{c}(1+\delta_{ec})} h^{\delta_{ec}^{2}} \phi_{e}(h,\alpha) d\alpha dh$$
(8)

and total human capital supplied to occupations r and c is

$$R^{s} = \sum_{e,a} s_{e}s_{a}L_{aer}$$
 and $C^{s} = \sum_{e,a} s_{e}s_{a}L_{aec}$

where s_e and s_a are the share of workers of education level e and age a in the population.

On the demand side unit wages in occupations r and c are determined by equation (7):

$$\log w_r = \log A_r + (\rho - 1) \left(\log C^d - Y(R^d, C^d) \right)$$
$$\log w_c = \log A_c + (\rho - 1) \left(\log R^d - Y(R^d, C^d) \right)$$

Equilibrium is reached at $w = (w^r, w^c)$ such that contour function $h \to \alpha^*(h, w)$ produces the labor supply equal to the labor demand in both occupations.

D Model Estimation

Each worker *i* employed in occupation *o* obtains wage $\log w_i = \log w_o + \log h_i$, where h_i is the amount of human capital held at the worker's age *a* and education level *e*. The model counterparts to the data moments are

$$\overline{\log w}_{eao} = \mathbb{E} \left[\log w_i | i \in \{e, a, o\} \right]$$
$$= \log w_o + \mathbb{E} \left[\log h_i | i \in \{e, a, o\} \right]$$
$$\overline{\log w^2}_{eao} = \mathbb{E} \left[(\log w_i)^2 | i \in \{e, a, o\} \right]$$
$$= (\log w_o)^2 + 2 \log w_o \mathbb{E} \left[\log h_i | i \in \{e, a, o\} \right] + \mathbb{E} \left[(\log h_i)^2 | i \in \{e, a, o\} \right]$$

where if we assume that threshold condition (8) is satisfied and g is any continuous function:

$$\mathbb{E}\left[g(h_i)|i \in \{e, a, r\}\right] = \frac{\int_0^\infty \int_0^{\alpha^*(h)} g(h, \alpha)\phi_e(h, \alpha) \mathrm{d}\alpha \mathrm{d}h}{s_{aer}}$$
$$\mathbb{E}\left[g(h_i)|i \in \{e, a, c\}\right] = \frac{\int_0^\infty \int_{\alpha^*(h)}^\infty g(h, \alpha)\phi_e(h, \alpha) \mathrm{d}\alpha \mathrm{d}h}{s_{aec}}$$

and the shares of workers sorting into r and c are

$$s_{aer} = \int_0^\infty \int_0^{\alpha^*(h)} \phi_e(h, \alpha) d\alpha dh$$
$$s_{aec} = \int_0^\infty \int_{\alpha^*(h)}^\infty \phi_e(h, \alpha) d\alpha dh$$

Age bins are young (up to 30), middle-aged (between 31 and 45), and senior (46 to 55). In the estimation, each age period is weighted by its duration, which vary depending on education level: non-HEGs enter the labor market at 20, and their age is a = 1 for 11 years. Earnings during that time are therefore weighted by $\sum_{t=0}^{10} \beta^t$. HEGs enter the

labor market later, at 24 years, so a = 1 is weighted by $\sum_{t=0}^{6} \beta^{t}$. In subsequent ages, the weighting accounts for the differential start: middle-age is weighted by $\sum_{t=11}^{25} \beta^{t}$ and $\sum_{t=7}^{21} \beta^{t}$ for non-HEGs and HEGs respectively, and senior age by $\sum_{t=26}^{35} \beta^{t}$ and $\sum_{t=22}^{31} \beta^{t}$. Resulting from the differential weighting of age bins for non-HEGs and HEGs, contour functions $h \to \alpha_{e}^{*}(h)$ depend on education level $e \in \{0, 1\}$.

The parameters $(\delta_{eo})_{e,o}$ are calibrated on all years between 1991 and 2020. Average log wage by age, education level and occupation is computed and smoothed across age using a LOESS (Locally Estimated Scatterplot Smoothing) method, weighted by the number of workers in each age cell. Calibrated $(\hat{\delta}_{eo})_{e,o}$ are then computed with equation

$$\widehat{\delta}_{eo} = \frac{\widehat{\log w_{3eo}} - \widehat{\log w_{2eo}}}{\widehat{\log w_{2eo}} - \widehat{\log w_{1eo}}}$$

To estimate the rest of the parameters, the distance between the data and model moments is minimized. The minimization problem is

$$\min_{\Gamma} \sum_{\substack{e \in \{0,1\}\\o \in \{r,c\}}} (\overline{s}_{eo}(\Gamma) - \widehat{s}_{eo})^2 + \sum_{\substack{e \in \{0,1\}\\a \in \{1,2,3\}\\o \in \{r,c\}}} \left(\overline{\log w}_{eao}(\Gamma) - \widehat{\log w}_{eao}\right)^2 + \sum_{\substack{e \in \{0,1\}\\a \in \{1,2,3\}\\o \in \{r,c\}}} \left(\overline{\log w}_{eao}^2(\Gamma) - \widehat{\log w}_{eao}^2\right)^2$$

The model is estimated with an MPEC method (Su and Judd (2012)), so the minimization is performed under the constraints:

$$R^s = R^d$$
 and $C^s = C^d$

which implicitly depends on w.

Computing moments $(\overline{\log w}_{eao}, \overline{\log w^2}_{eao}, s_{eo})_{e \in \{0,1\}, a \in \{1,2,3\}, o \in \{r,c\}}$ requires solving for the contour functions (α_0^*, α_1^*) such that supply of workers in both occupations is equal to demand from firms.

E Counterfactuals

	$\Delta s_{e,c}$	$\Delta \log w_{e,1}$	$\Delta \log w_{e,3}$	$\Delta \frac{\log w_{e,3}}{\log w_{e,1}}$
2009-2011				
(h, α) distrib + % HEG	-0.22	-0.2	-0.16	0.02
2018-2020				
(h, α) distrib + % HEG	-0.28	-0.2	-0.22	0.0

Table 13: Additional Counterfactual sorting and wage - HEGs

Notes: Source: EE cross-section. Author's own calculations.

	$\Delta s_{e,c}$	$\Delta \log w_{e,1}$	$\Delta \log w_{e,3}$	$\Delta \frac{\log w_{e,3}}{\log w_{e,1}}$
2009-2011				
(h, α) distrib + % HEG	0.0	-0.1	-0.09	0.01
2018-2020				
(h, α) distrib + % HEG	-0.02	-0.14	-0.14	0.01

 ${\bf Table \ 14:} \ {\rm Additional \ Counterfactual \ sorting \ and \ wage \ - \ non-HEGs}$

Notes: Source: EE cross-section. Author's own calculations.