The Decreasing Returns to Experience for Higher Education Graduates

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Abstract

This article evidences the flattening of wage dynamics for higher education graduates in France between the cohorts entering the labor market in 1998 versus 2010. Postgraduates in the latter cohorts enjoy 10% less labor income over their first seven years on the labor market than postgraduates in the former cohort. The difference in average yearly wage growth is 2.2 percentage points between the two cohorts. I decompose variations in wage growth between cohorts by occupation, and find a strong relation between the influx of new graduates in an occupation and the flattening of wage progression in that same occupation, suggesting congestion is causing the flattening. I show two mechanisms are at play behind congestion: access to managerial positions, which reduced over time, and field of study-occupation mismatch, which bears an increasing weight on young graduates' wages over time.

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JEL Codes: I21, I23, I24, J17, J24, J31

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1 Introduction

Higher education graduates' early career outcomes have recently become the focus of a large and wide-spanning literature in economics. The evidence points to a worsening of outcomes, both in terms of unemployment and labor market earnings. This paper examines higher education graduates' wage dynamics over their first seven years in the labor market in France. I perform the analysis by comparing cohorts, i.e. groups of individuals who enter the labor market at the same time, but not necessarily at the same age. I show wage progression has flattened for higher education graduates from recent cohorts, while it has not for other education levels. I evidence a mechanism of congestion to explain the wage dynamics slowdown: as France has experienced a large education expansion in the 2000s, more higher education graduates enter the labor market every year. Occupations in which the influx of graduates is the largest are the ones in which wage progression slows down the most. I highlight two mechanisms of congestion: access to managerial positions and field of study-occupation mismatch.

The literature traditionally focuses on the 'scarring effect' of recessions on new labor market entrants, by showing that entering the labor market under poor economic conditions translates to persistent higher unemployment and lower wages. 'Unlucky' cohorts experience these effects up to 15 years after labor market entry (Schwandt and von Wachter (2019), von Wachter (2020)). Gregg and Tominey (2005) show the scarring effect experienced by unlucky cohorts is due to exposure to unemployment. The effect of a recession may not be the same everywhere, nor for everyone: Genda et al. (2010) compare the United States and Japan and find different effects depending on the country: low-educated men in Japan suffer persistent negative effects on their careers, while low-educated Americans face only temporary effects. Brunner and Kuhn (2014) differentiate the analysis by socio-professional category in Austria and show that the recession particularly affected blue-collar workers, as they are stuck in low-quality jobs longer than white-collar workers. Stevens (2008) shows the negative effects of entering the labor market in a recession fade out after seven years on the labor market for low-skilled workers in Germany. In France, Gaini et al. (2013) study cohorts leaving the school system between 1982 and 2010 and conclude that entering the labor market in a recession results in a lower short-term employment rate. Studies show college-educated workers who graduate in a recession tend to enter lower level occupations (Kahn (2010)), and lower paying employers (van den Berge and Brouwers (2017), van den Berge (2018)) than those who graduate under better economic conditions. Catch-up can occur through job mobility to better paying employers (Oreopoulos et al. (2012)). Another strand of literature highlight the link between the college wage premium, i.e. the average wage gaps between college (or university) educated workers and the others, and the relative supply of these two categories of workers. Katz and Murphy (1992) and Card and Lemieux (2001) explain the increasing college wage premium of the 1970s and 1980s in the US through the decline in relative supply of college graduates in the labor market. Goldin and Katz (2008) describe the race between education and technology which results in an equilibrium college wage premium. In France Verdugo (2014) shows that unlike in the US, the university wage premium declines continuously between 1969 and 2008, while the relative supply of university graduates rises.

In this article, I compare the career outcomes of three cohorts, who left school in 1998, 2004 and 2010, over their first seven years in the labor market in France. I evidence a slowdown in the returns to potential experience: yearly average wage progression flattens between the 1998 and 2010 cohorts. Workers who graduated with long high education (masters and PhD, i.e. degrees which take at least four years to complete) are particularly affected: their yearly entry wage growth is 4.6% for the 1998 cohort and only 2.4% for the 2010 cohort. Short (four years and less) higher education graduates go from 3.7% of yearly average growth to 2.3%. This flattening occurs before the Great Recession: the 2004 cohort is also affected. As noted by Rothstein (2021) in the US for the employment of cohorts who enter the labor market after 2005, the flattening observed in France suggests a structural decrease in higher education graduates' wage returns to experience, which cannot be fully accounted for by the economic cycle. **?** evidence the flattening of returns to experience in France, using the same dataset as this paper. The flattening of lifetime earnings is also evidenced by the life-cycle literature (Manovskii and Kambourov (2005), Guvenen et al. (2017), Ashworth et al. (2021), Guvenen et al. (2021)). Building on this literature and the welfare analysis proposed in von Wachter (2020), I compute the present discounted value of annual earnings seven years after entry into the labor market for each cohort, and find that it is 6% lower for the 2004 cohort and 10% lower for the 2010 cohort than it is for the 1998 cohort.

To understand the higher education graduates' wage progression slowdown, I follow the literature aforementioned and focus the analysis at the occupation level. I find a striking relationship between the influx of new graduates in an occupation between 1998 and 2010 and a slowdown in wage progression in that occupation. This fact suggests congestion may be behind the wage progression slowdown. As the supply of higher education graduates increases between 1998 and 2010, demand falls behind and young graduates are trapped in low-paying jobs. This hypothesis is further reinforced by changes in occupation composition in the French active population over the period: the share of higher education graduates employed as highly qualified professionals decreases between 1999 and 2011, while the share employed as mid-level professionals increases. The literature has show the former occupation to be associated with abstract task, which require a high level of education, while the later involves routine tasks (?, Albertini et al. (2017), Patel (2020)). The shift of higher education graduates from the former to the latter in the general population points to the same congestion evidence as the analysis on young graduates.

This paper contributes to the literature in two ways. First, it augments the growing body of research that points to a structural decrease in young higher education graduates' labor income, and evidence it in the specific context of France. Second, it thoroughly lays out the congestion mechanism behind the structural decrease income and describes how it plays out over young graduates' early careers, through access to managing positions and mismatch.

I explore two mechanisms behind congestion. First, I show that access to managerial positions has reduced over the first seven years in the labor market between 1998 and 2010. This is in line with Kwon et al. (2010)'s findings that young workers are not promoted to managers as much during recessions. I also show that managerial positions are correlated with a higher wage, but that this correlation has weakened since the end of the 1990s. Young higher education graduates are therefore confronted with an extensive margin (they become managers at a lower frequency) and an intensive margin (being a manager does not bring the wage increase it used to). The second mechanism I evidence pertains to mismatch in first employment. Liu et al. (2016) have shown that mismatch between the field of study and industry increases in times of recessions for young college graduates, and this increase is responsible in part for the persistence of their wage loss. I slightly modify their definition of mismatch to study it at the field of study-occupation level, as the classification of occupation in France captures precisely the type of tasks carried out in each job and is therefore very informative as to whether a field of study is suitable for the job. Differently from Liu et al. (2016), I find no increase in mismatch: rather, its distribution has narrowed between 1998 and 2010. I do find that the impact of mismatch on subsequent wages has strengthened, and its effect is more long-lasting for the 2010 cohort than it used to be for the 1998 cohort, despite increased mobility between jobs and occupations. This finding is robust to a different specification of mismatch. I also test the effect of the initial unemployment rate on subsequent wages, based on the identification strategy described in Oreopoulos et al. (2012) and von Wachter (2020), which uses local variation in the unemployment rate in the first year in the labor market. Unlike most of the literature, I find no significant effect of initial unemployment on wage progression, which further suggests a structural trend in flattening wage progression for higher education graduates. An alternative explanation for congestion would be adverse selection, i.e. that the productivity of higher education graduates lowers between 1998 and 2010, prompting employers to give fewer pay raises to younger workers. Such a decrease in productivity could have happened in two ways. First, as a higher education expansion took place in France in the 2000s, it may be that standards for admissions lowered. As a results, the average unobserved heterogeneity of higher education graduates wold have weakened. Second, the education expansion could have affected human capital acquisition, either through the increase in the number of students or through the changes the French education system underwent to adapt to the expansion. I test this hypothesis in several ways: by using grade retention, a proxy for unobserved heterogeneity, approximating the variance of unobserved heterogeneity with that of observed wages and decomposing the wage progression between fields in which the number of graduates has increased and those in which it did not. In all of these tests, I find this hypothesis to be inconsistent with the data, making congestion the more likely explanation. This conclusion is consistent with Argan et al. (2022)'s work, that uses a finite mixture model to identify latent worker types, and shows that adverse selection is not a likely explanation for the returns to education flattening, because student selection actually improved over time in France.

The paper is organized as follows. Section 2 presents the data and empirical facts, section 4 describes the empirical strategy and occupational decomposition of wage progression. Section 5 exposes the main results, section 6 the mechanisms, and section 7 the welfare analysis. Robustness checks and tests for alternative explanations are in section 8. 9 concludes.

2 Data and Empirical Facts

2.1 The French labor market between 1999 and 2011

The wage dynamics studied in this paper fall within wider trends in the French labor market between 1998 and 2017. Table 1 uses INSEE census data[1] to provide a general overview of the changes in the composition of the educational levels and occupations of the working population between 1999 and 2011. On the supply side, the share of higher education graduates in 1999 was 24.6% of the working-age population. In 2011, this share is 36.4%, a gain of almost 3 million individuals. The share of individuals with a high school degree has also increased but to a lesser extent. On the firm side, one can obtain a general picture of demand changes by investigating changes in the working population's occupational composition. Occupations in France are classified by INSEE on two levels. The first level identifies

[1] Downloadable from https://www.insee.fr/fr/statistiques/1893185

six broad occupations: Farmers, Craftsmen, Retailers, and business owners, Factory workers, Employees, Mid-level professionals, and Highly qualified professionals. The second level identifies 31 sub-occupations. Table 19 in Appendix A details the two levels of occupation categorization. Table 1 shows the number of workers employed in each of these occupations, in total and by education level. Mid-level and Highly qualified professionals are the two occupations whose headcount increased the most between 1999 and 2011. The headcount of Employees and Craftsmen, shopkeepers and business owners stagnates, while it decreases in the Farmers and Factory workers occupations.

The educational composition within occupations also changes over the period, as the share of higher education graduates rises in every occupation. The largest change occurs among the Mid-level professionals: it employs 43.7% of higher education graduates in 1999 and 55.1% in 2011. In absolute terms, it gains more higher education graduates over the period than any other occupation, and in particular than Highly qualified professionals, which employs almost exclusively higher education graduates.

Table 1: Education Levels by Occupations within French active population in 1999 and 2011

	1999			2011			Difference	
Occupation	Nb (k)	% HS	% HE	Nb (k)	% HS	% HE	HS (k)	HE (k)
Farmers	532	16.1	7.5	344	28.3	18.4	12	23
Craftmen, retailers, business owners	1407	15.0	14.9	1367	21.4	23.9	82	116
Factory workers	5827	6.2	2.7	5162	15.1	6.8	418	193
Employees	6587	16.7	10.5	6522	24.8	20.5	516	646
Mid-level professionals	5100	21.8	43.7	5905	21.1	55.1	134	1026
Highly qualified professionals	2802	10.6	76.3	3726	9.2	82.0	47	920
Total	22255	14.2	24.6	23026	19.0	36.4	1210	2925

Nb (k): Number of individuals in thousands

HS: High School degree, HE: Higher Education degree

2.2 The CEREQ data

The Generation Surveys are produced by the Center for Studies and Research on Qualifications (CEREQ). Every six years, the CEREQ surveys a representative sample of school leavers at different education levels, from high school dropouts to PhD 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. CEREQ conducts its surveys on a given cohort every two or three years. For instance, the 2010 cohort is surveyed in 2013, 2015 and 2017. Only individuals who responded to all three surveys are considered here. Additional data sources are from INSEE, the French National Statistic Institute, and include county level unemployment rates[2] and unemployment rate by education level[3].

The three surveys are unequal in terms of the number of individuals surveyed (Table 2): there are twice as many individuals surveyed from 1998 versus the 2010 cohort. To account for these differences, and any selection effect that may arise from attrition, the Generation Surveys provide the analyst with a weighting per individual so that each survey is representative of the population of young French workers. I adapt this weighting to weigh not only individuals, but also their spells: since the data are presented as individual-spell observations the weight of individuals who change spells frequently is very large (interim workers for instance). To avoid this I weigh spells of individuals who change status several times a year according to spell length. The entire analysis will be weighted by these modified weights.

The analysis focuses on employment spells and starting (or entry) wage obtained by young workers hired at the beginning of these spells, the changes in which is compared between the 1998, 2004 and 2010 cohort by levels of education. Each individual's first spell starts the month after graduation or after they left school if they did not graduate. The surveys also provide the last wage obtained at the end of each spell, but no intermediary wage. I choose to focus on entry wage, because this is invariant to the duration of the employment spell. Using the INSEE consumer price index series, I compute wages in constant prices in euro 2017.

[2] Downloadable from https://www.insee.fr/fr/statistiques/2012804

[3] Downloadable from https://www.insee.fr/fr/statistiques/5359491?sommaire=5359511&q=T304

I exclude from the analysis spells in which individuals are under 16 years old, as well as the employment spells for which the monthly starting wage is less than € 200 or more than € 20,000. The analysis focuses on job spells for which the location (at the county level) and firm sector are known. The number of individuals and spells in the final sample are presented in Table 2.

Table 2: Number of individuals and spells by cohort

	Gen 1998	Gen 2004	Gen 2010
Number of individuals	13673	9633	7500
Number of spells	64078	45530	35367
Number of employment spells	28095	22082	16428

Source: CEREQ Generation Surveys. Author's own calculations.

Individuals' main characteristics are described in Table 3: there are no major differences between cohorts in terms of the average age of school leavers, gender, or the average number of (employment) spells.

Table 3: Age, gender, and individual number of spells by cohorts

	Gen 1998	Gen 2004	Gen 2010
Average age at entry on labor market	21.6	21.2	21.3
% Men	51.1	52.6	51
Average number of spells	4.9	5.3	5.2
Average number of employment spells	2.1	2.4	2.3

Source: CEREQ Generation Surveys. Author's own calculations.

The analysis is focused on educational attainment and occupation. From the education information provided in the survey, I group individuals into four education levels: no degree (left the education system without finishing secondary school), secondary education (obtained either a general high school degree, or a vocational degree), short higher education (obtained a degree in less than four years, either a bachelor or a technical degree), and long higher education (obtained a degree in more than four years, either masters or PhD). Table 4 presents the composition of each cohort by levels of education: the share of long higher education graduates (or postgraduates) is larger in the 2010 cohort than in the 2004 and 1998 cohorts, while the shares of short tertiary graduates and secondary school graduates are lower. The share of individuals without a degree is higher in the 2010 cohort. The Generations surveys show the polarization of educational provision between 1998 and 2010.

Table 4: Education level shares by cohort

Education level (%)	Gen 1998	Gen 2004	Gen 2010
No degree	8.9	7.9	17.2
High school degree	52.3	53	42.7
Short higher educ. degree	28.1	27.6	23.3
Long higher educ. degree	10.7	11.5	16.9
Total	100	100	100

Source: CEREQ Generation Surveys. Author's own calculations.

Table 5 shows the share of first job's occupation by cohort. The share of Highly qualified professionals increased between the 1998 and 2010 cohorts. The share of Mid-level professionals has also increased, albeit at a slower pace. As in the general population (Table 1), the share of factory workers has decreased, and the share of employees has stagnated. Because farmers represent too small a share of the employment spell, these spells are excluded from the rest of the analysis.

Table 5: Occupation shares by cohort

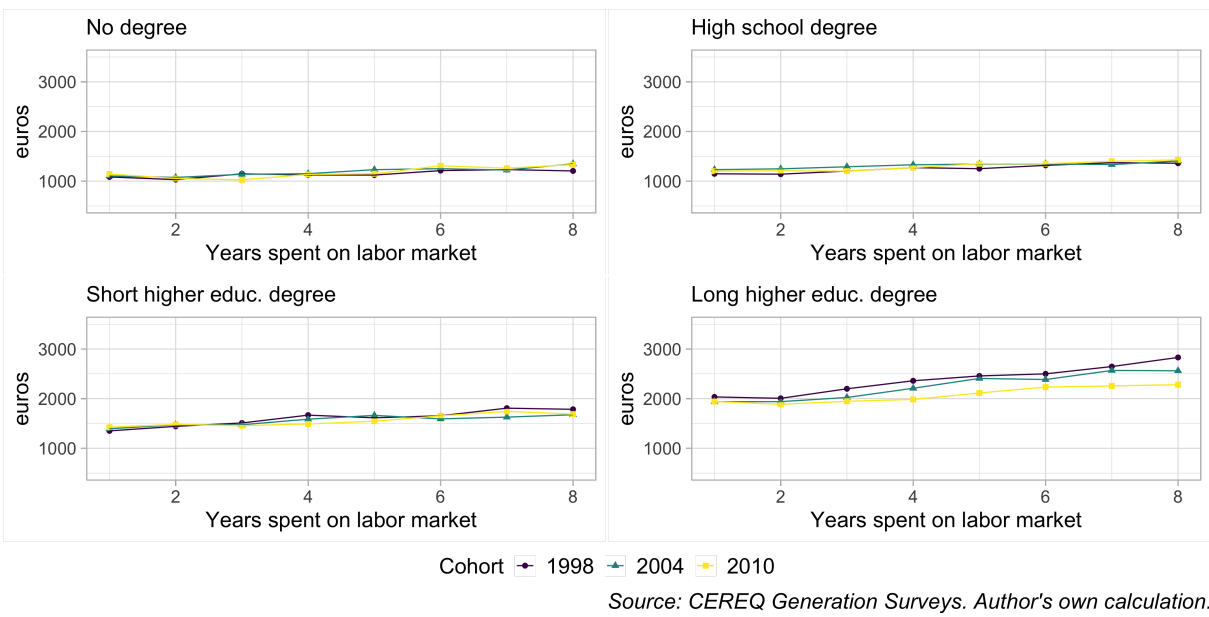
Occupation (%)	Gen 1998	Gen 2004	Gen 2010
Farmers	0.7	0.2	
Craftmen, Shopkeepers, Business owners	1.1	0.7	0.1
Factory workers	32.7	30.9	24.6
Employees	28.2	26.9	26.4
Mid-level prof.	25.2	29.9	30.3
Highly qualified prof.	12.1	11.4	18.6
Total	100	100	100

Source: CEREQ Generation Surveys. Author's own calculations.

3 Wage dynamics

Figure 1 plots average starting wages by cohort and education level over time, based on entry wages reported by individuals in the Generation Surveys. Individuals with no degree and high school graduates display the same wage dynamics across cohorts. But higher education graduates, and especially long higher education graduates, register changes in their wage dynamics between the 1998 and 2010 cohorts: younger cohorts benefit from slower wage growth. For long higher education graduates, the slowdown becomes more pronounced over time: the three cohorts begin their working lives with similar entry wages, and then diverge. While the 1998 cohort enjoys a significant average increase in starting wage from their second year in the labor market, the 2004 cohort's average starting wage significantly increases after three years in the labor market, and that of the 2010 generation after four years. The result is that the 2010 cohort is significantly behind its predecessors, a gap that persists beyond the 2010-2012 crisis period (years 1 to 3 for the 2010 generation), without any catching up taking place in the subsequent years available in the survey.

Figure 1: Average entry wage over time, by cohort and education level



In the next section, I develop an empirical strategy to understand the supply and demand forces behind the wage progression slow down observed in Figure 1.

4 Strategy

The empirical strategy framework is the following: individual i, of a given cohort and education level, enters employment contract $j = J(i,t)$ in year t. Each contract j is characterised by the firm's location and industry. Entry monthly wage obtained by i under contract with j in year t is w_{ijt}. In a first step, I estimate equation (1) by Ordinary Least Squares (OLS) to compute the average wage growth rate by cohort and education level:

$$\log w_{ijt} = \alpha + \sum_e \mathbb{1}_{[educ_i=e]}\beta_{eg} \times a_t + e_i + g_i + l_i + s_j + \epsilon_{ijt}. \tag{1}$$

$\log w_{ijt}$ is the logarithm applied to entry wage w_{ijt}, a_t is the number of years since leaving school (between 1 and 8), e_i is a fixed effect for educational attainment, g_i a fixed effect for the individual gender, l_i is a fixed effect for the location ('departement', or county level) and s_j a fixed effect for the industry within which the contract takes place.

The estimator β_{eg} is computed by education level e and cohort g. It measures the average increase in entry wage per year, for each cohort and education level, controlling for variations in gender, industry, and region. Comparing β_{eg} and $\beta_{eg'}$ between two cohorts g and g' requires making the following identification assumption: the distribution of unobserved heterogeneity is the same for all cohorts. This assumption will be maintained for the rest of the analysis.

A large part of the literature has identified different outcomes by occupations (Genda et al. (2010), Brunner and Kuhn (2014), Stevens (2008)), which is why he second part of the analysis focuses on wage progression by occupation, at the granular level that identifies 31 different occupations. To understand the change in β_{eg} across cohorts in terms of supply and demand, I run a second regression (2) that computes average wage growth by occupation, in addition to cohort and education level:

$$\log w_{ijt} = \alpha + \sum_e \mathbb{1}_{[educ_i=e]} \sum_g \mathbb{1}_{[occ_j=p]}\gamma_{egp} \times a_t + +e_i + g_i + l_i + s_j + \epsilon_{ijt}. \tag{2}$$

Variables are the same as in equation (1), and γ_{egp} now measures average wage growth by occupation, education level and cohort. Both regressions (1) and (2) are run separately for each cohort.

In this framework, the estimate β_{eg} is a weighted average of occupation level estimates $(\gamma_(egp))_p$. The following decomposition can therefore be carried out, for a given level of education e :

$$\hat{\beta}_{e,2010} - \hat{\beta}_{e,1998} = \sum_p n_{e,2010,p} \times \hat{\gamma}_{e,2010,p} - \sum_p n_{e,1998,p} \times \hat{\gamma}_{e,1998,p}$$

Where $n_{e,1998,p}$ et $n_{e,2010,p}$ are the respective shares of each occupation p within education level e and the 1998 and 2010 cohorts. In the spirit of an Oaxaca-Blinder decomposition, I introduce the cross term $\sum_p n_{e,2010,p} \times \hat{\gamma}_{e,1998,p}$ to obtain:

$$\hat{\beta}_{e,2010} - \hat{\beta}_{e,1998} = \sum_p (n_{e,2010,p} - n_{e,1998,p}) \times \hat{\gamma}_{e,1998,p} \\ - \sum_p n_{e,1998,p} \times (\hat{\gamma}_{e,2010,p} - \hat{\gamma}_{e,1998,p}) \tag{3}$$

The first term $(n_{e,2010,p} - n_{e,1998,p}) \times \hat{\gamma}_{e,1998,p}$ is an extensive margin, or a composition effect: the change in the slope of entry wage growth that is due to changes the share of occupation p within new hires. The second term $n_{e,2010,p} \times (\hat{\gamma}_{e,2010,p} - \hat{\gamma}_{e,1998,p})$ is an intensive margin, or a price effect: the part of the change in the slope that is due to the change in the slope for specific occupation p, holding constant the share of each occupation in new hires. This decomposition seeks to separate a pure demand or composition effect (changes in the occupation of new hires between cohorts, i.e. the extensive margin) from a supply and demand equilibrium effect (changes in the distribution of education levels within individuals, captured by the intensive margin).

5 Results

Estimation results for equation (1) are presented in Table 6. Coefficients for entry-level wage growth are significant for all cohorts and levels of education. The rate of growth for entry wages earned by individuals with no degree and high school graduates rises slightly between the 1998 and the 2010 cohorts. Long higher education graduates experience more sustained growth in wage than other education levels, but it is less pronounced for the 2004 and 2010 cohorts than the 1998 cohort: the long 1998 higher education graduates enjoy a 4.6% yearly growth in entry wage, but the 2010 graduates only experience a 2.4% growth. Short higher education graduates experience the same decline in growth: from 3.7% to 2.3% between the 1998 and 2010 cohorts. Note that the education fixed effect does not display the same downward trend as wage growth: the differential between higher education graduates and individuals with no degree is higher within the 2010 cohort (Average wage is 37.5% and 60.5% higher with a short and long higher education degree than no degree) that it is within the 1998 cohort (32.1% and 59.1%). Since short and long higher education graduates face the same trend in wage progression, they are pooled for the remaining of the analysis.

Table 6: Log entry wage regressed on number of years spent on the labor market by education level (Eq (1))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
High school degree	0.138***	0.204***	0.17***
	(0.013)	(0.018)	(0.016)
Short higher educ. degree	0.321***	0.344***	0.375***
	(0.014)	(0.018)	(0.017)
Long higher educ. degree	0.591***	0.546***	0.605***
	(0.016)	(0.021)	(0.018)
Years × No degree	0.027***	0.037***	0.037***
	(0.003)	(0.003)	(0.003)
Years × High school degree	0.026***	0.019***	0.03***
	(0.001)	(0.001)	(0.002)
Years × Short higher educ. degree	0.037***	0.025***	0.023***
	(0.002)	(0.002)	(0.002)
Years × Long higher educ. degree	0.046***	0.045***	0.024***
	(0.003)	(0.003)	(0.003)
FE gender	✓	✓	✓
FE location	✓	✓	✓
FE industry	✓	✓	✓
Observations	37 785	27 656	20 130
R^2	0.325	0.244	0.283

*p<0.1; **p<0.05; ***p<0.01

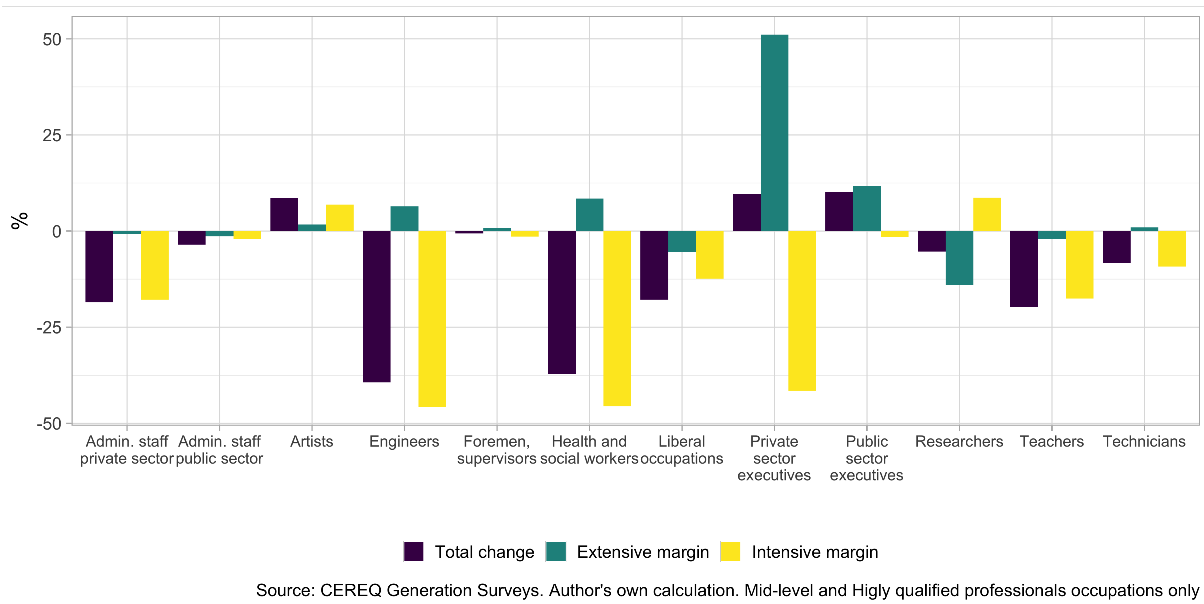
All occupations except Farmers

Source: CEREQ Generation Surveys. Author's own calculations.

Next, I run regression (2) to decompose average wage growth by occupation, at the most granular level. I then apply decomposition (3), and plot the results for all higher education graduates (long and short) in Figures 2 and 3.

Figure 2 shows there is significant heterogeneity in margins depending on occupations. They can be classified into two broad types: the first and most prominent category comprises engineers, foremen and supervisors, health and social workers, private and public sector executives. Their extensive margin is positive, meaning there has been an increase in the relative number of hires in these occupations between cohort 1998 and cohort 2010. But their intensive margin is below zero. In many cases, it outweighs the extensive margin, so the total contribution of the occupation to wage progression is a slowdown. The second category of occupations displays a negative extensive margin: public and private administrative staff, liberal occupations, researchers and teachers. The price effect for these occupations is not as clear-cut as in the first category, but it remains relatively small.

Figure 2: Average wage growth decomposition by education level and disaggregated occupation - Higher education graduates



All the occupations that experience an increase in the share of new hires between the 1998 and 2010 cohorts are the ones that display the largest decrease in wage growth. Figure 3 shows this relationship with a scatter plot, by projecting occupations onto the extensive/intensive margin space. This finding is consistent with a theory of diminishing marginal returns in occupations: the influx of new employment contracts in these occupations, driven by an increase in the supply of higher education graduates, leads to a drop in marginal productivity of individuals who have recently entered the market, which translates into lower returns to experience.

Figure 3: Average wage growth decomposition by education level and disaggregated occupation - Long higher education graduates

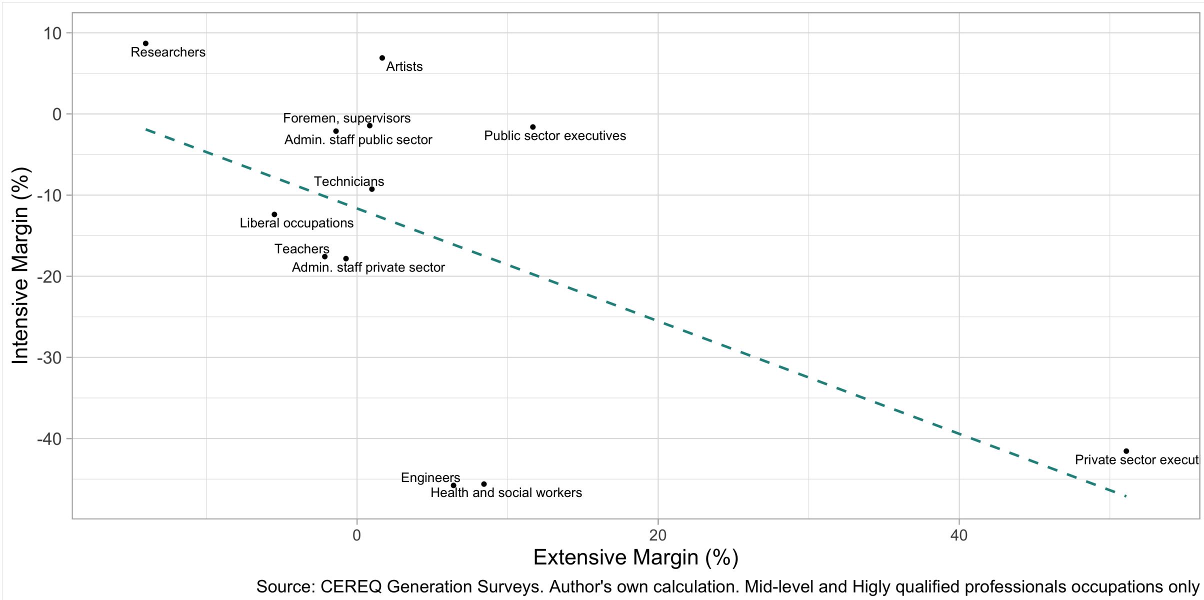


Figure 3 suggests high education graduates from the 2010 cohort suffer from a congestion effect:in the occupations where in the influx of new graduates is the largest, returns to experience fall significantly. In the next section, I explore the mechanisms behind congestion. I first focus on the effect of a recession at labor market entry, which materializes as a decrease in firm demand on labor markets. Second, I look at promotions to managing positions. Third, I explore the role of degree-occupation mismatch.

6 Mechanisms

6.1 Unemployment rate at entry on labor market

The first candidate mechanism to wage progression slowdown is the labor market state at cohort entry. It is already the object of a large and thorough literature that studies the effect of initial labor market conditions on medium and long term careers outcomes (von Wachter (2020), Oreopoulos et al. (2012), Gaini et al. (2013)). This literature evidences a 'scarring effect', that is, the persistent influence of bad labor market conditions at entry on future wages and employment. Since the 2010 cohort enters the labor market in times of economic turmoil, it may very well be what is driving the flattening of their wage progression compared to previous cohorts. To explore whether this is a valid mechanism, I borrow the estimation framework that is most used in the literature, by regressing log wage on the initial local unemployment rate, separately by cohort and education level:

$$\log w_{ijt} = \sum_a \mathbb{1}_{[a_t=a]} \tau_{get} u_{0l_i} \times a + a_t + g_i + l_i + s_j + \epsilon_{ijt}. \tag{4}$$

u_{0l_i} is the unemployment rate at individual i's location in year 0 (the year individual i leaves school). Identification is provided by the variation in local unemployment rates u_{0r} by location (at 'departement' or county level). In most of the literature (von Wachter (2020)), observation of different cohorts in the same year allows to separately identify a calendar year fixed effect from an experience fixed effect (the number of years since entry on the labor market). Cohorts are too spread over time in the Generation Surveys to allow for this separate identification, so instead I run regression (4) separately by cohort and education level, and capture fixed effect a_t that accounts both for experience and calendar year.

Table 7 presents the results from regression (4) for higher education graduates and all cohorts. The same Table 20 for high school graduates0 is presented in Appendix B. A 1% higher unemployment rate has a negative, albeit rarely significant, impact in all years 1 to 8 on cohorts 2004 and 2010 wage levels. Estimates for the 1998 cohort are more surprising, as they are all positive, but again, not always significant. All in all, these results suggest local unemployment rate at market entry has little impact on higher education graduates' subsequent wages in France. This results is the opposite of what is found in other countries such as Norway (Liu et al. (2016)) or Canada (Oreopoulos et al. (2012)).

Table 7: Log entry wage regressed on unemployment rate at entry - Higher education (Eq (4))

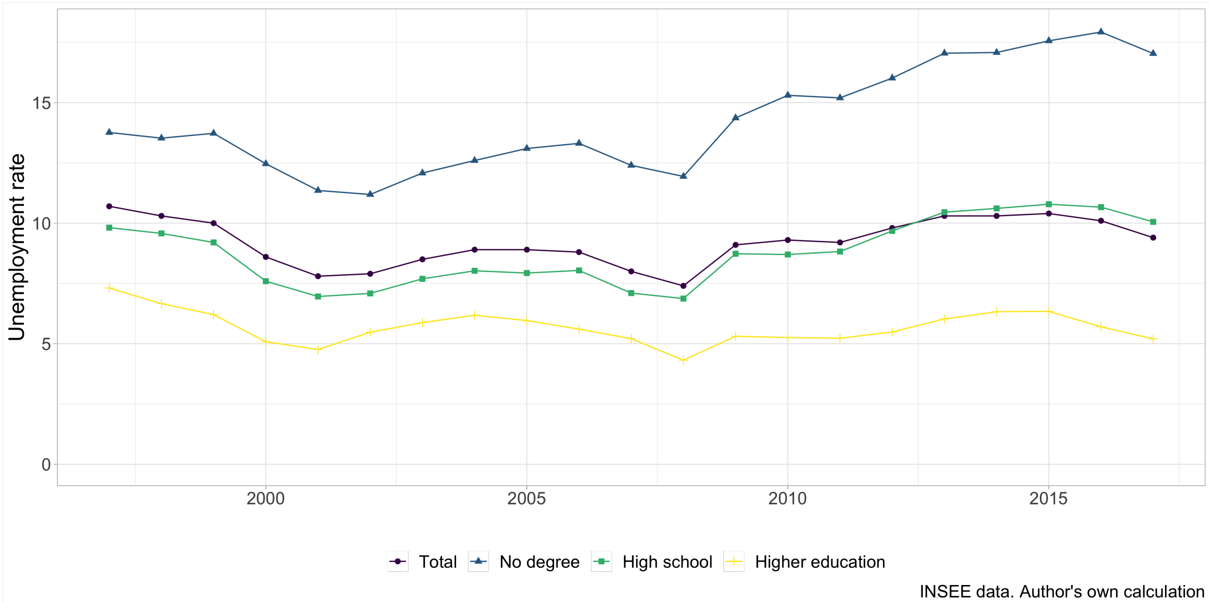
	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Year 1 × Unemployment	0.004	-0.009	-0.004
	(0.005)	(0.007)	(0.008)
Year 2 × Unemployment	0.012**	-0.015*	-0.008
	(0.005)	(0.008)	(0.008)
Year 3 × Unemployment	0.000	-0.004	-0.015
	(0.006)	(0.009)	(0.009)
Year 4 × Unemployment	0.006	-0.001	-0.018*
	(0.006)	(0.009)	(0.01)
Year 5 × Unemployment	0.002	-0.001	-0.010
	(0.006)	(0.008)	(0.009)
Year 6 × Unemployment	0.020***	-0.015	-0.031***
	(0.006)	(0.01)	(0.01)
Year 7 × Unemployment	-0.004	0.000	-0.006
	(0.006)	(0.01)	(0.01)
Year 8 × Unemployment	0.004	-0.023**	-0.028***
	(0.007)	(0.01)	(0.011)
FE experience, gender, location, industry	✓	✓	✓
Observations	14 464	12 979	11 123
R^2	0.214	0.157	0.171

*p<0.1; **p<0.05; ***p<0.01

Source: CEREQ Generation Surveys and INSEE data. Author's own calculations.

There can be two reasons why local initial unemployment has little traction on educated workers' subsequent wages in France: first, the overall unemployment rate (that I use at the local level in Table 7's specification') and the higher education graduates' unemployment rate (that is not available at the local level) are significantly different, as shown in Figure 4. The national higher education graduates' unemployment rate varies little over the period and is about half of the overall national unemployment rate.

Figure 4: Unemployment rate by education level

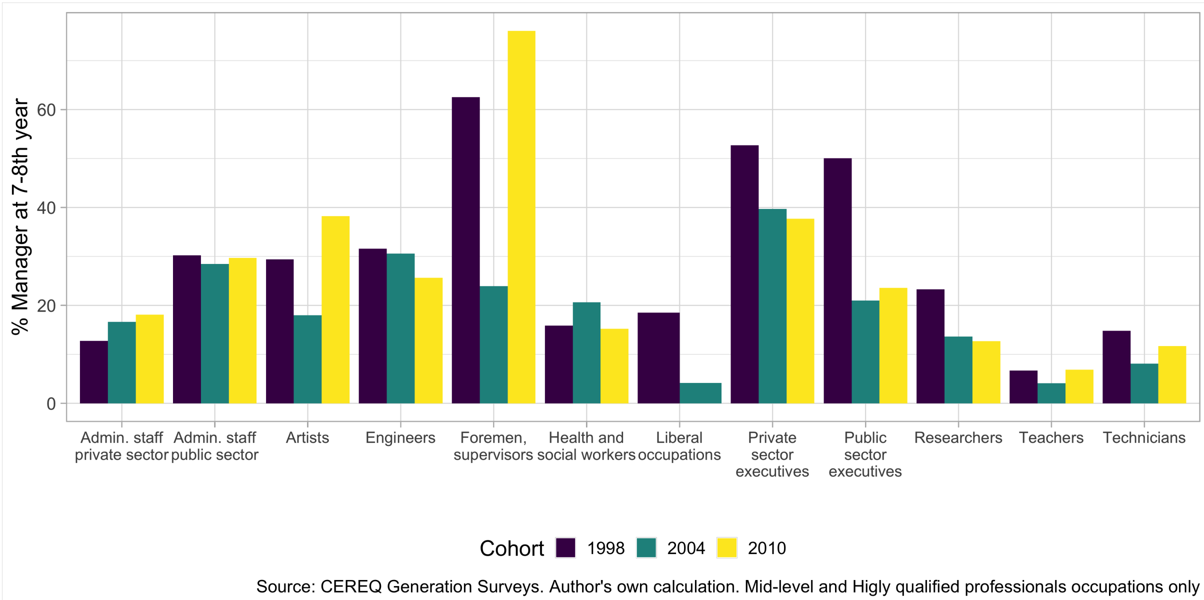


The other reason is linked to our data: because we only have three cohorts in the dataset, the variation across locations in the local unemployment rate is only relevant in the years 1998, 2004 and 2010. Some summary statistics in these years reveal there is little variation across locations: in 1998, 80% of locations are between 7.0% and 12.9% of the local unemployment rate. In 2010 they are between 6.9% and 10.9%.

6.2 Promotion to managerial positions

A second mechanism I explore to explain the higher education graduates' wage slowdown is the change in access to managerial positions. I follow Kwon et al. (2010), who show that in Sweden and the US, cohorts who enter the labor market in a boom get promoted faster, which accounts for a substantial part of their wage growth. In the Generation Surveys, I use the question 'Do you manage a team?' to know whether employees have reached a manager stage, regardless of their occupation. Figure 5 shows the share of manager hires in the 7th and 8th year after entry on the labor market, by cohort and occupation. Engineers, health and social workers, private and public sector executives, researchers and technicians' share of managers decreases between the 1998 and the 2010 cohort.

Figure 5: Average wage growth decomposition by education level and disaggregated occupation Higher education graduates



To find out whether fewer manager hires translate into lower wages for the 2010 cohort, I estimate the following by cohort:

$$\log w_{ijt} = \sum_{e} \mathbb{1}_{[educ_i = e]} \left(\eta_{ge} + \zeta_{ge} \times M_{ijt} \right) + M_{ijt} + e_i + g_i + l_i + s_j + \epsilon_{ijt}. \tag{5}$$

Dummy M_{ijt} indicates whether the contract entered by individual i and firm j requires i to manage a team. The coefficient of interest is ζ_{ge}, as it captures the added benefit of being hired as a manager.

The OLS estimates for η_{ge} and ζ_{ge} are presented in Table 8. η_{ge} captures average baseline wage growth by education level. As in the main specification presented in Table 6, baseline wage growth is decreasing across cohorts for higher education graduates. It is also clearly increasing between cohort 1998 and cohorts 2004 and 2010 for individuals with no degree, although this trend was not present in the main specification. Given that estimate ζ_{ge} is below zero for this level of education, it suggests accessing managing positions lowers the wage of uneducated individuals from the 2010 and 2010 cohorts. Accessing a managing position has little significant impact on high school graduates. However, it has a positive (between 3.4% and 1.4%) and significant impact on higher education graduates, although it decreases for younger cohorts.

Table 8: Log entry wage regressed on number of years spent on the labor market by education level and managing position (Eq (5))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
No degree × Year	0.029***	0.039***	0.038***
	(0.003)	(0.004)	(0.003)
High school degree × Year	0.025***	0.017***	0.029***
	(0.001)	(0.001)	(0.002)
Higher educ. degree × Year	0.031***	0.023***	0.021***
	(0.001)	(0.002)	(0.002)
No degree × Year	-0.005	-0.028***	-0.008*
	(0.004)	(0.009)	(0.004)
High school degree × Year	0.005**	0.004	0.005
	(0.002)	(0.003)	(0.003)
Higher educ. degree × Year	0.039***	0.03***	0.014***
	(0.002)	(0.003)	(0.004)
FE manager, education, gender, location, industry	✓	✓	✓
Observations	37 430	26 659	20 093
R^2	0.314	0.238	0.274

*p<0.1; **p<0.05; ***p<0.01

Source: CEREQ Generation Surveys. Author's own calculations.

Taken together, Figure 5 and Table 8 evidence two margins of impact from accessing a managing position. First, as the share of new manager hires decreases between the 1998 and 2010 cohorts, the latter cohort earns less of the wage bonus given by these positions than the former. Second, the wage bonus associated with being hired as a manager itself is divided by more than two between the 1998 and 2010 cohorts. Hence the higher education graduates who become managers among the 2010 cohorts obtain less of a wage increase than they would have, had they graduated in 1998.

6.3 Field of study-Occupation match quality

Match quality between degree and employment plays an important role in the determination of medium-term wage for higher education graduates, as evidenced by Liu et al. (2016) in the case of Norway. Their analysis shows poor initial economic conditions translate into deteriorated matching between graduates' field of study and first job's industry. In turn, this increased mismatch negatively impacts medium-term wages. In France, in addition to the early 2010s recession, there has been an increase and diversification of the educational supply (Dupray and Moullet (2010)) among the 2004 and 2010 cohorts, which may also have affected the quality of initial matching the first job for these two cohorts.

Table 9 lists fields of studies available to higher education students in France and their distribution among each cohort. Despite the diversification of educational provision, the distribution remains fairly stable between the 1998 and 2010 cohorts. Two notable changes are the decline in the share of 'Arts, Literature and Communication' as well as 'Humanities and Law', and the rise in 'Economics, Trade and Management', and 'Mathematics and Sciences'. The same Table 21 for high school graduates is presented in Appendix B.

Table 9: Field of study shares by cohort - Higher education graduates

Share of graduates (%)	Gen 1998	Gen 2004	Gen 2010
Agriculture, Fishing, Forestry	2.7	3.6	2.7
Arts, Literature, Communication	15	13.7	10.6
Civil Engineering, Construction	2.3	2	2
Community and Personal Services	22.7	22.4	21.4
Economics, Trade, Management	19.4	22.6	24.1
Flexible Materials	4.2	3.8	2.4
Humanities and Law	14.6	12.9	10.7
Mathematics and Sciences	5.7	5.9	12.1
Mechanics, Electricity, Automation	13.4	13	13.9
Total	100	100	100

Source: CEREQ Generation Surveys. Author's own calculations.

Thanks to the detailed level of information provided by the Generation Surveys, I depart from Liu et al. (2016)'s set up and conduct the mismatch analysis at the field of study-occupation survey. The reason is that occupations in France hold much more information on the content of work that is actually performed by individuals, while industries employ a variety of occupations and pay a wide range of different wages. I retain the spirit of Liu et al. (2016)'s analysis by defining match quality based on the first job held. I obtain a measure of average wage by field of study and occupation by estimating the following equation by cohort and education level:

$$\log w_{ijt} = \sum_s \mathbb{1}_{[FoS_i=s]} \sum_p \mathbb{1}_{[occ_j=p]} \delta_{geps} + a_t + g_i + l_i + s_j + \epsilon_{ijt}. \tag{6}$$

FoS_i the field of study chosen by individual i. Estimation of equation (6) on the subset of first hires provides wage average $\tilde{\delta}_{geps}$. To define a measure of matching, rank the $\left(\tilde{\delta}_{geps}\right)_s$ for each given cohort, education level and occupation combination. Define the 'best matched' field of study as the highest δ_{geps} in that cell:

$$s^* = \arg\max_s \delta_{geps}.$$

Matching quality between a field of study s and occupation p is defined as the distance between s and s^*:

$$M_{geps} = \delta_{geps^*} - \delta_{geps}$$

M_{geps} is equal to zero if $s = s^*$ and below zero otherwise. The larger M_{geps} is the greater the mismatch. M_{geps} is a flexible measure of (mis)matching: a field of study s may be poorly matched with an occupation p for a given cohort g and education level e, but it may be a good match for any other occupation p', cohort g' or education level e'. M_{geps} also accounts for the distance in terms of average wage at first employment between fields of study. An alternative measure of mismatch, borrowed from Liu et al. (2016), is tested in section 8 and yields qualitatively similar results.

Table 10 shows the distribution of M_{geps} by cohort and education level in terms of median and interquartile deviation, weighted by individuals. Since individuals with no degree do not choose a field of study, they are excluded from the present analysis. Median matching quality has slightly decreased for high school graduates between the 1998 and 2010 cohorts but has consistently increased for higher education graduates. Higher education graduates' interquartile range has also reduced. The distribution of mismatched has narrowed for higher education graduates between the 1998 and 2010 cohorts, and its median level has declined. An increased mismatch is unlikely to be the driver of slower wage progression for higher education graduates.

Table 10: Match quality: median and interquartile range by cohort and education level

Education level	Statistic	Gen 1998	Gen 2004	Gen 2010
High school degree	p50	0.06	0.07	0.08
	[p25-p75]	[0.05,0.11]	[0.02,0.13]	[0.04,0.15]
Higher educ. degree	p50	0.13	0.08	0.04
	[p25-p75]	[0,0.2]	[0,0.19]	[0,0.14]

Source: CEREQ Generation Surveys. Author's own calculations.

To assess the impact of initial match quality on entry wages in subsequent years I estimate the following equation, at cohort and education levels:

$$\log w_{ijt} = \sum_a \mathbb{1}_{[year_t=a]} \bar{M}_{gep_is_i} \lambda_{gea} + a_t + g_i + l_i + s_j + \epsilon_{ijt} \tag{7}$$

Estimated coefficient $\hat{\lambda}_{gea}$ is differentiated per year. Measure $\bar{M}_{geps}$ is the normalized match quality[4]. Equation (7) measures the average impact of mismatch on log-wage, differently by cohort, education level and years of experience. Within a cohort and education level, all individuals face the same conditions every year, captured by a fixed effect, hence the only variation between individuals in this regression is due to the difference in initial matching quality.

The estimated coefficients $\hat{\lambda}_{geps}$ for higher education graduates are presented in Table 11 for long higher education graduates only (the same Table 22 for high school graduates is in Appendix B). The impact of match quality is generally positive and significant, meaning a higher M_{geps} in absolute value (that is, a higher mismatch) negatively impacts wage. Unsurprisingly, match quality has a strong effect on wages in the first years for all cohorts: one standard deviation of match quality increases wages by 10% for the 1998 and 2010 cohorts in the first year, and by 13.5% for the 2004 cohort. The effect wanes over time at different rates depending on cohort: it is systematically smaller for the 1998 cohort than the 2010 cohort in all years except year 3. In year 8, the effect is at 3.6% for the 1998 cohort but still at 6.5% for the 2010 cohort. Table 22 in the appendix shows mismatch for high school graduates displays no such trends.

[4] It has mean 0 and standard deviation 1 for all cohorts and education levels.

Table 11: Log entry wage regressed on match quality by year and education level - Higher Education (Eq (7))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Year 1 × Mismatch	-0.097***	-0.133***	-0.093***
	(0.006)	(0.007)	(0.006)
Year 2 × Mismatch	-0.079***	-0.081***	-0.074***
	(0.006)	(0.008)	(0.007)
Year 3 × Mismatch	-0.030***	-0.087***	-0.054***
	(0.008)	(0.01)	(0.01)
Year 4 × Mismatch	-0.045***	-0.068***	-0.034***
	(0.01)	(0.011)	(0.011)
Year 5 × Mismatch	-0.049***	-0.069***	-0.048***
	(0.01)	(0.011)	(0.012)
Year 6 × Mismatch	-0.060***	-0.054***	-0.038***
	(0.011)	(0.013)	(0.012)
Year 7 × Mismatch	-0.045***	-0.061***	-0.094***
	(0.011)	(0.014)	(0.015)
Year 8 × Mismatch	-0.046***	-0.096***	-0.061***
	(0.013)	(0.017)	(0.015)
FE experience, gender, location, industry	✓	✓	✓
Observations	13 661	11 766	10 399
R^2	0.242	0.205	0.208

*p<0.1; **p<0.05; ***p<0.01

Source: CEREQ Generation Surveys. Author's own calculations.

Initial match quality plays an increasingly significant role in slowing down the salary progression of higher education graduates between the 1998 and 2010 cohorts, not because mismatch has inflated, but because its impact on subsequent salary levels has increased. This could be explained by mobility: if the 2010 cohort would change jobs less frequently than the 1998 cohort, the initial match quality may play a role in determining hiring wages for a longer time. However, average number of employment spells for higher education graduates is 1.7, 2.1 and 2.1 for cohorts 1998, 2004 and 2010 respectively. The two last cohorts are changing jobs as much, if not more, than the 1998 cohort. To explore the mobility hypothesis in more detail, it is necessary to analyse the structure of transitions between occupations of each generation. If the 2004 and 2010 cohorts switch occupations less often than the 1998 cohort, initial matching quality's impact may increase as individuals remain stuck in occupations to which their degree is not adapted. However, this hypothesis is again mildly contradicted by the data: among the higher education graduates, those who never change occupation in the first seven years on the labour market account for 49.6%, 48.5% and 48.0% of the 1998, 2004 and 2010 cohorts, respectively. Therefore changes in occupations are more common among the 2004 and 2010 cohorts. The increased impact of initial match quality could be explained by the rise in the number of graduates in the labour market: mismatched individuals in the 2004 and 2010 cohorts may find it harder to access higher-paying jobs for their degree's field of study, despite their increased job mobility, as each year a new cohort enters the labour market, increasing competition for the best jobs. Because the supply of higher education graduates is smaller in the late 1990s and early 2000s, the 1998 generation faces less competition and is able to make up for any low initial match quality.

7 Welfare Analysis

To assess the impact of the wage progression slow down, I follow Schwandt and von Wachter (2019) and von Wachter (2020) to compute cumulative earning loss for the 2004 and 2010 cohorts to the 19998 cohort. Table 12 shows the present discounted value of earnings for each cohort over the first seven years in the labor market after entry, as well as the change compared to the 1998 cohort. Present discounted values are computed at gender and education levels. Not all education levels suffer from a loss in the present discounted value of annual earnings: individuals with no degree and high school graduates enjoy an increase in earnings, especially the 2004 cohort. Higher education graduates, and in particular long higher education graduates, suffer from a large loss however: the 2010 cohort earns 10.1% less than the 1998 cohort over their first seven years in the labor market. Men are especially affected: they earn 10.5% less. These losses are likely to be larger over the long run.

Table 12: Loss in Present Discounted Value of annual earnings in first 7 years after entry on the labor market

	Gen 1998	Gen 2004		Gen 2010	
	PDV (€)	PDV (€)	% Change to Gen 1998	PDV (€)	% Change to Gen 1998
All					
No degree	72365	75256	4.0	73799	2.0
High school degree	80606	84765	5.2	83085	3.1
Short higher educ. degree	99733	98262	-1.5	99382	-0.4
Long higher educ. degree	146181	137462	-6.0	131465	-10.1
Women					
No degree	63666	67564	6.1	66115	3.8
High school degree	72085	77134	7.0	75882	5.3
Short higher educ. degree	92473	92116	-0.4	92146	-0.4
Long higher educ. degree	131451	126658	-3.6	120483	-8.3
Men					
No degree	76738	79174	3.2	77828	1.4
High school degree	86886	90389	4.0	89325	2.8
Short higher educ. degree	111460	107946	-3.2	108471	-2.7
Long higher educ. degree	158442	148423	-6.3	141828	-10.5

PDV earnings computed using a 5% discount rate

Change in PDV computed in percentage of Gen 1998's PDV

Source: CEREQ Generation Surveys. Author's own calculations.

8 Robustness tests

8.1 Sample representativity

The Generation Survey report individual wages when a transition occurs: either a job-to-job transition or a transition from or to unemployment. As such, they provide an unbalanced panel: individuals who do not transition in any given year are not observed in that year. Moreover, individuals who go through many transitions are observed often, and hence weigh in in the analysis. On the contrary, a market entrant who finds a job in their first year and keeps that job until the end of the panel reports their entry wage only once. It is therefore important to check for external validity whether individuals who rarely transition experience the same trends in wage growth as those who often transition. To do so, I use two features of the Generation Surveys. First, current wages are reported for all employed individuals in the last interview session of each cohort, which occur in 2005, 2011 and 2017. These cross-sectional observations can be used to check whether all higher education graduates are affected by the wage progression slow down. Second, exit wages are also reported for every employment sequence. I use this information to check whether the entry wage progression slowdown is compensated for by pay raises during employment spells.

Table 13 shows the average observed wage in the 2005, 2011 and 2017 cross-sections, by cohort and education level. Cross-sectional wages for higher education graduates have decreased between the 1998 and 2010 cohorts, with a particularly strong effect for long higher education graduates. They have slightly increased for non)graduates and high school graduates. Table 13 confirms that wage growth has slowed for all individuals in the 2004 and 2010 cohorts, including those in long-term employment.

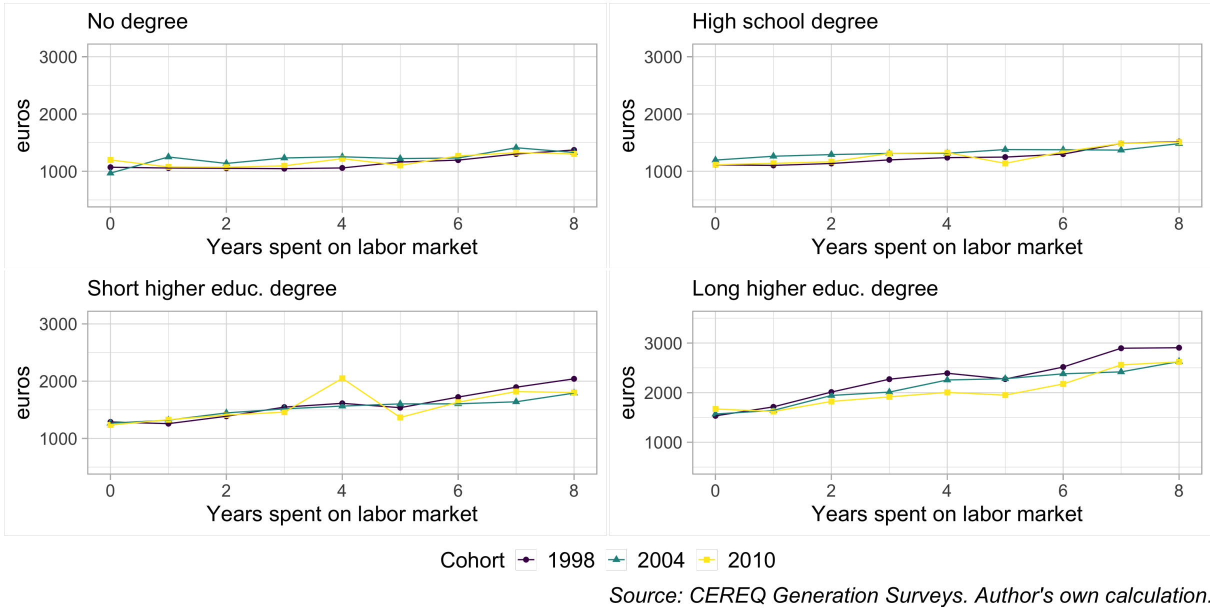
Table 13: Average observed wage at end of survey, by cohort and education level

Education	Gen 1998	Gen 2004	Gen 2010
No degree	1325	1341	1357
High school degree	1499	1472	1508
Short higher educ. degree	1918	1775	1826
Long higher educ. degree	2902	2594	2567

In constant 2017 euros

Figure 6 is the equivalent of Figure 1 but plots exit wages instead of entry wages. Exit wages are higher than hiring wages for all cohorts and education levels, but exhibit the same slowdown for higher education graduates. This is consistent with a job ladder framework in which individuals can negotiate higher entry wages in their next job based on their previous job's exit wage.

Figure 6: Average end of employment spell wage over time, by cohort and education level



8.2 Unobserved heterogeneity

8.2.1 Testing the identifying assumption

Section 5's results are based on the identifying assumption that the distribution of unobserved quality is the same across cohorts. A way to test this identifying assumption is to use a proxy for unobserved heterogeneity provided in the Generation Surveys, namely grade retention before the start of secondary school (a strategy also used in Dupray and Moullet (2010)). Grade retention is frequent in France, and is used as a means to strengthen a weak student's learning abilities by having them repeat a grade. The literature on grade retention in France finds small and positive effect on scores (d'Haultfoeuille (2010), Gary-Bobo et al. (2016)) but negative effects on wages (**?**). I build a dummy for grade retention from the reported age at the start of secondary school. The normal age in 6th grade is 11 years old, hence any individual who was older than 11 in 6th grade must have repeated a grade in primary school. In the Generation Surveys, 23% of the 1998 cohort, 12% of the 2004 cohort, and 13% of the 2010 cohort repeated a grade in primary school. The practice of grade retention scales back in the 2000s, so the share of individuals who were retained in each cohort is not indicative of the unobserved heterogeneity distribution in this cohort. However grade retention can be used as a control for unobserved heterogeneity within each cohort, in the following way: if the identifying assumption was wrong, and indeed the distribution of unobserved heterogeneity had shifted to the left between the 1998 and the 2010 cohort, then average unobserved ability among individuals who were retained would be lower in the 2010 than in the 1998 cohort, especially since the threshold for retention is lower for the former. If this were the case, we would observe an impact of lowered ability for the 2010 cohort with the following equation:

$$\log w_{ijt} = \alpha + \pi_g \times a_t + \chi_g r_i \times a_t + \rho_g r_i + e_i + g_i + l_i + s_j + \epsilon_{ijt}. \tag{8}$$

Variable r_i is equal to 1 if individual i repeated a grade in primary school, and zero otherwise. π_g measures baseline wage progression by cohort g. χ_g estimates the penalty in wage progression associated with having retained a grade. ρ is a fixed effect for having been retained. Equation (8) is estimated by cohort.

Table 14 displays the estimates for ρ_g, π_g and χ_g by cohort. The static fixed effect of retention on wage is close to zero and non-significant for all cohorts. The average yearly wage progression is around 3% for all cohorts. Having repeated a grade does indeed impose a penalty on wage progression, but it is small (around 1%) and does not change across cohorts. Therefore the prediction from a shift in the distribution of unobserved heterogeneity is not verified, and these results are consistent with the identifying assumption.

Table 14: Log entry wage regressed on dummy for grade repeat and years spent on the labor market by education level (Eq (8))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Retention	0.000	0.016	0.013
	(0.008)	(0.011)	(0.013)
Year	0.033***	0.026***	0.030***
	(0.001)	(0.001)	(0.001)
Year × Retention	-0.008***	-0.011***	-0.008***
	(0.002)	(0.002)	(0.003)
FE education, gender, location, industry	✓	✓	✓
Observations	37 785	27 599	19 992
R^2	0.325	0.244	0.282

*p<0.1; **p<0.05; ***p<0.01

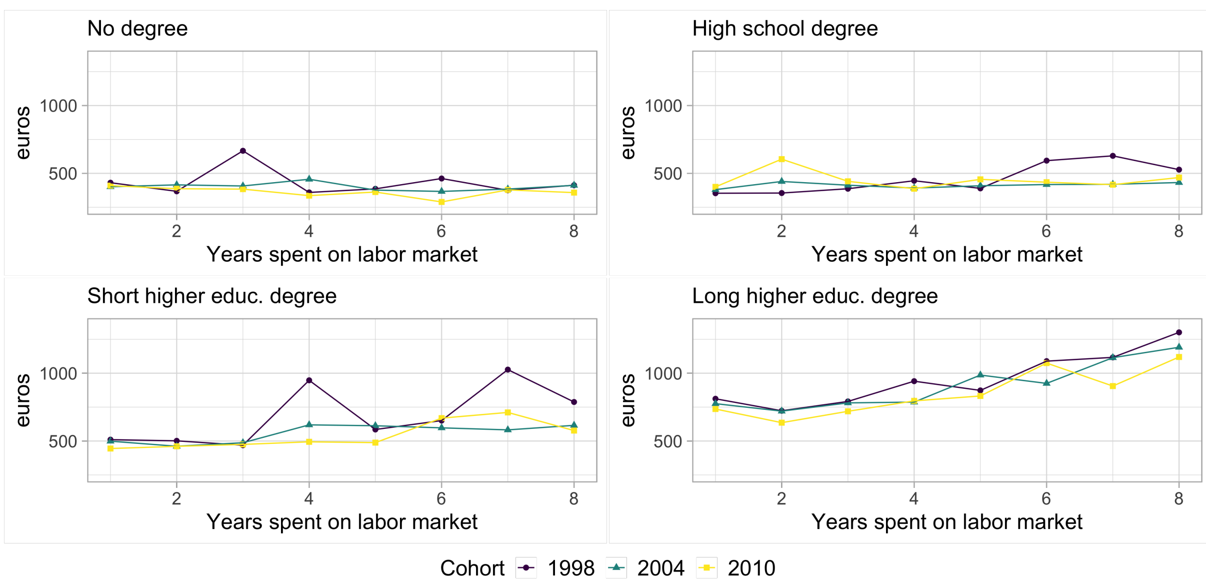
Only individuals whose age is known in 6th grade are included

Source: CEREQ Generation Surveys. Author's own calculations.

8.2.2 Sorting

Even under the identifying assumption that the unobserved heterogeneity distribution has remained unchanged between cohorts, changes in sorting into education levels may have occurred. If more individuals graduate from higher education, the average unobserved ability among higher education graduates is likely to decrease, and its variance is likely to increase. A concurrent explanation for the wage progression slowdown would then be that employers gradually learn about the lower abilities of the more recent higher education graduates. If it were true, however, we should see an increase in higher education graduates' wage standard deviation, as the individuals with the highest unobserved ability still sort into higher education. Figure 7 plots the wage distribution variance by cohort, education level and years of experience. Although variance increases over time for both short and long higher education graduates, it does so more for the 1998 than the 2004 and 2010 cohorts.

Figure 7: Entry wage standard deviation over time, by cohort and education level



Source: CEREQ Generation Surveys. Author's own calculation.

The combination of average wage progression slow down and decrease in standard deviation across cohorts is inconsistent with a lower higher education graduates' unobserved ability, under the assumption that overall unobserved ability distribution has not shifted between cohorts. But it is consistent with a story of congestion, in which even the high ability higher education graduates from 2010 see too few increases in entry wage for wage progression to pick up and the standard deviation of wage to increase.

8.3 Human capital accumulation

Another concern for the interpretation of the baseline results presented in section 5 is the possible changes in human capital acquired in higher education. With the education expansion described in Table (1), the human capital acquisition could have changed in two ways: first, the quality of acquired human capital could have worsened due to larger groups of students in class or lack of equipment and/or instructors and advisors to cater to the greater number of students. To check whether this is the case, I allocate fields to two groups, based on Table 9: one in which the share of students has risen between the 1998 and 2010 cohorts, the other in which it has lowered. I then compare their rate of wage progression. The second way whereby human capital acquisition could have changed is through the evolution of higher education institutions. Higher education students in France can choose to study either at a public university, which have generally no selection at entry, or at a business or an engineering school, which are often private and selective. Universities' education provision has evolved since the 1990s, with the Bologna process formatting and the introduction of new courses to adapt to the education expansion's new demands. Meanwhile, the curricula have remained globally the same in business and engineering schools. A comparison of wage progression rates by different types of schools and universities should therefore inform us of whether changes in educational provision impact wage progression for higher education graduates.

To address the first concern, namely that an education expansion affects lessens human capital accumulation at school, I split the set of fields of study into two: on the one hand the fields for which the share of higher education graduates has increased between the 1998 and 2010 cohorts (Economics, Trade, Management/Mathematics and Sciences/Mechanics, Electricity, Automation), and on the other hand, the fields for which it has decreased. This former group is referred to as the 'popular fields'. If an education expansion does damage human capital accumulation, we should observe an important slow down in wage progression for graduates in popular fields between the 1998 and 2010 cohorts. To check for this, I run the following regression on the subset of high school graduates by cohort:

$$\log w_{ijt} = \nu_g p_i + \tau_g p_i \times a_t + a_t + g_i + l_i + s_j + \epsilon_{ijt}. \tag{9}$$

p_i is a dummy for whether the individual graduates from a popular field. ν_g is the static effect on the log wage of graduating from a popular field, and τ_g is the dynamic effect.

Table 15 shows the estimates ν_g and τ_g from regression (9). Graduating from a popular field has a positive but non-significant static effect on wages, and a positive and significant dynamic effect, between 1p.p and 1.4p.p extra wage growth per year, for all cohorts. We observe no clear decreasing trend in wage progression for graduates from a popular field between the 1998 and 2010 cohort: the dynamic effect moves only by .2p.p at most and is highest for the 2004 cohort. Therefore we can exclude the worsened human capital accumulation explanation as a main driver of the wage progression slow down.

Table 15: Log entry wage regressed on years spent on the labor market by type of field - Higher education graduates (Eq (9))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Popular field	0.009	0.000	0.007
	(0.012)	(0.013)	(0.013)
Year × Popular field	0.012***	0.014***	0.010***
	(0.003)	(0.003)	(0.003)
FE experience, gender, location, industry	✓	✓	✓
Observations	12 588	7 455	11 114
R^2	0.164	0.15	0.172

*p<0.1; **p<0.05; ***p<0.01

Individuals whose field of study is unknown are excluded

Source: CEREQ Generation Surveys. Author's own calculations.

The second concern for human capital accumulation relates to the type of human capital that is acquired in higher education. Course offers at the university have changed between 1998 and 2010: they have diversified, and course length has aligned with the Bologna process. To check if this could have had an impact on wage progression, I compare university graduates' wage growth to engineering and business schools. Table 16 shows the share of graduates from each type of institution by cohort. The share of university graduates has risen, while the share of business and engineering school graduates has dropped.

Table 16: Degree type shares among higher education graduates

Degree type (%)	Gen 1998	Gen 2004	Gen 2010
Business school	14.6	11.3	9.2
Engineering school	24.3	22.5	19.9
University	61.2	66.2	70.9

To measure wage progression by type of degree, I run the following regression:

$$\log w_{ijt} = \alpha + \nu_g d_i + \tau_g d_i \times a_t + g_i + l_i + s_j + \epsilon_{ijt}. \tag{10}$$

d_i is the type of institution where higher education graduates i obtained their degree: university, business school, or engineering school. ν_g captures the type of degree's static effect, and τ_g the dynamic effect.

Table 17 presents estimates for ν_g and τ_g. Wage progression decreases between cohort 1998 and 2010 for all degree types, by approximately the same relative amount. We can conclude that the change in nature of human capital accumulation at university is unlikely to drive the total slow down in wage progression.

Table 17: Log entry wage regressed on years spent on the labor market by type of degree - Higher education graduates (Eq (10))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Engineering school	0.115^{***}	0.03	0.079^{**}
	(0.04)	(0.042)	(0.035)
University	0.056	-0.103^{***}	-0.035
	(0.035)	(0.036)	(0.031)
Years × Business school	0.079^{***}	0.061^{***}	0.038^{***}
	(0.008)	(0.008)	(0.007)
Years × Engineering school	0.054^{***}	0.037^{***}	0.027^{***}
	(0.006)	(0.006)	(0.005)
Years × University	0.038^{***}	0.047^{***}	0.025^{***}
	(0.004)	(0.004)	(0.003)
FE gender, location, industry	✓	✓	✓
Observations	2 926	4 081	5 891
R^2	0.3	0.228	0.202

*p<0.1; **p<0.05; ***p<0.01

Individuals whose degree type is unknown are excluded

Source: CEREQ Generation Surveys. Author's own calculations.

8.4 Mismatch measure

To test whether the measure of mismatch used in section 6 is robust, I borrow from Liu et al. (2016) and test an alternative measure of mismatch, which is equal to 1 if the field of study ranks in the three least earning fields in first employment and zero otherwise, within occupation, cohort and education.

$$M_{geps} = \mathbb{1}_{[R_s \geq 3]}$$

Where R_s is the rank of s when fields of study are ranked from lowest to highest, by occupation, education level, and cohort.

I run regression (7) using this alternative measure of mismatch. The results for higher education graduates are presented in Table 18 the same Table 23 is presented in Appendix C for high school graduates. As with its baseline definition, mismatch has a negative, although not always significant, impact on average wage at every level of experience, and for all cohorts. The effect is particularly strong for the 2010 cohort, with up to a 16% penalty on the average wage in the year 7.

Table 18: Log entry wage regressed on alternative match quality by year and education level - Higher Education (Eq (7))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Year 1 × Mismatch	-0.147***	-0.149***	-0.216***
	(0.013)	(0.014)	(0.014)
Year 2 × Mismatch	-0.166***	-0.123***	-0.179***
	(0.014)	(0.016)	(0.017)
Year 3 × Mismatch	-0.103***	-0.099***	-0.107***
	(0.017)	(0.021)	(0.022)
Year 4 × Mismatch	-0.077***	-0.099***	-0.113***
	(0.02)	(0.022)	(0.025)
Year 5 × Mismatch	-0.093***	-0.122***	-0.123***
	(0.022)	(0.024)	(0.026)
Year 6 × Mismatch	-0.164***	-0.035	-0.103***
	(0.026)	(0.029)	(0.027)
Year 7 × Mismatch	-0.086***	-0.052*	-0.166***
	(0.026)	(0.03)	(0.03)
Year 8 × Mismatch	-0.070**	-0.193***	-0.127***
	(0.028)	(0.033)	(0.03)
FE experience, gender, location, industry	✓	✓	✓
Observations	14 063	12 245	10 906
R^2	0.235	0.177	0.203

*p<0.1; **p<0.05; ***p<0.01

Source: CEREQ Generation Surveys. Author's own calculations.

9 Conclusion

Young higher education graduates, and especially postgraduates, in France experience an increasing delay in wage growth in their early career, which translates into at 10% loss between the 1998 and 2010 cohorts. The decomposition of average wage growth by occupation points to a congestion mechanism. Both the fewer occurrence of managing position contract and the increased impact of field of study-occupation mismatch on wages give weight to the congestion hypothesis. Meanwhile, various tests show a decrease in unobserved productivity of higher education graduates is unlikely. The loss evidenced in the analysis is likely to endure in the later stage of the higher education graduates' career. Public policies should focus on tackling the congestion that causes this phenomenon, mostly on the demand side, by developing programs that support and value young graduates' skills in firms.

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A Data and Empirical Facts

Table 19: French Occupation Classification

Level 1	Level 2
Farmers	Large farm operators
	Medium farm operators
	Small farm operators
Craftmen, retailers, business owners	Craftmen
	Retailers
	Business owners
Factory workers	Drivers
	Agriculture workers
	Unskilled workers - Handicraft
	Unskilled workers - Manufacturing
	Skilled workers - Handicraft
	Skilled workers - Manufacturing
	Skilled workers - Transport
Employees	Staff - public sector
	Admin. staff - private sector
	Commercial staff - private sector
	Direct service staff - private sector
	Police and military staff
Mid-level professionals	Admin Staff - public sector
	Admin. staff - private sector
	Clergy, clerics
	Foremen, supervisors
	Health and social workers
	Teachers
	Technicians
Highly qualified professionals	Artists
	Engineers
	Liberal occupations
	Private sector executives
	Public sector executives
	Researchers

B Mechanisms

Table 20: Log entry wage regressed on unemployment rate at entry, by education level - High school (Eq (4))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Year 1 × Unemployment	-0.004	-0.011*	-0.018
	(0.004)	(0.006)	(0.011)
Year 2 × Unemployment	-0.004	-0.010	-0.009
	(0.004)	(0.007)	(0.012)
Year 3 × Unemployment	-0.006	-0.008	-0.019
	(0.004)	(0.007)	(0.012)
Year 4 × Unemployment	-0.011***	-0.014**	-0.019
	(0.004)	(0.007)	(0.013)
Year 5 × Unemployment	-0.007*	0.002	-0.019
	(0.004)	(0.007)	(0.012)
Year 6 × Unemployment	-0.008*	-0.013*	-0.026**
	(0.004)	(0.007)	(0.012)
Year 7 × Unemployment	-0.007*	-0.020***	-0.015
	(0.004)	(0.007)	(0.012)
Year 8 × Unemployment	-0.011**	0.006	-0.024*
	(0.004)	(0.008)	(0.013)
FE experience, gender, location, industry	✓	✓	✓
Observations	20 731	13 935	7 474
R^2	0.161	0.14	0.151

*p<0.1; **p<0.05; ***p<0.01

Source: CEREQ Generation Surveys and INSEE data. Author's own calculations.

Table 21: Field of study shares by cohort - Higher school graduates

Share of graduates (%)	Gen 1998	Gen 2004	Gen 2010
Agriculture, Fishing, Forestry	5.9	5.1	4.9
Arts, Literature, Communication	10.5	9.5	9.3
Civil Engineering, Construction	6.1	7.9	6.6
Community and Personal Services	17.1	18.5	22.2
Economics, Trade, Management	18.1	21.2	21
Flexible Materials	7.9	9.4	8.2
Humanities and Law	9.8	4.2	7.3
Mathematics and Sciences	2.8	4	6.3
Mechanics, Electricity, Automation	20.4	20.2	14.1
Total	100	100	100

Source: CEREQ Generation Surveys. Author's own calculations.

Table 22: Log entry wage regressed on match quality by year and education level - High School (Eq (7))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Year 1 × Mismatch	-0.055***	-0.031***	-0.080***
	(0.005)	(0.006)	(0.009)
Year 2 × Mismatch	-0.035***	-0.036***	-0.043***
	(0.006)	(0.008)	(0.01)
Year 3 × Mismatch	-0.021***	-0.016*	-0.024**
	(0.006)	(0.008)	(0.012)
Year 4 × Mismatch	-0.040***	-0.041***	-0.044***
	(0.007)	(0.009)	(0.013)
Year 5 × Mismatch	-0.002	-0.007	-0.031***
	(0.007)	(0.009)	(0.011)
Year 6 × Mismatch	-0.011	0.003	-0.019
	(0.008)	(0.01)	(0.012)
Year 7 × Mismatch	-0.009	-0.002	-0.004
	(0.008)	(0.01)	(0.013)
Year 8 × Mismatch	-0.029***	0.015	-0.040***
	(0.008)	(0.011)	(0.013)
FE experience, gender, location, industry	✓	✓	✓
Observations	19 406	10 898	6 887
R^2	0.172	0.162	0.17

*p<0.1; **p<0.05; ***p<0.01

Source: CEREQ Generation Surveys. Author's own calculations.

C Robustness Tests

Table 23: Log entry wage regressed on alternative match quality by year and education level - High School (Eq (7))

	log entry wage		
	Gen 1998	Gen 2004	Gen 2010
Year 1 × Mismatch	-0.036***	-0.034***	-0.101***
	(0.011)	(0.012)	(0.018)
Year 2 × Mismatch	-0.033**	-0.018	-0.027
	(0.013)	(0.016)	(0.022)
Year 3 × Mismatch	-0.045***	-0.014	-0.028
	(0.015)	(0.018)	(0.026)
Year 4 × Mismatch	-0.075***	-0.054***	-0.007
	(0.016)	(0.019)	(0.029)
Year 5 × Mismatch	-0.011	-0.009	-0.019
	(0.017)	(0.019)	(0.027)
Year 6 × Mismatch	0.011	0.041*	-0.041
	(0.019)	(0.023)	(0.028)
Year 7 × Mismatch	-0.080***	-0.001	-0.045
	(0.019)	(0.023)	(0.029)
Year 8 × Mismatch	-0.081***	0.086***	-0.070**
	(0.02)	(0.026)	(0.031)
FE experience, gender, location, industry	✓	✓	✓
Observations	19 692	11 290	7 185
R^2	0.164	0.158	0.157

*p<0.1; **p<0.05; ***p<0.01

Source: CEREQ Generation Surveys. Author's own calculations.