Investing in Human Capital : Impact of Specialization for New Arrivants in the Labor Market*

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PRELIMINARY VERSION - Ongoing work

Abstract: This paper studies and quantifies the consequences of professional versus general schooling decisions. Theoretically, human capital can be split in two parts : a "general" and a "specialized" (meaning task or occupation-specific) one. Taking into account jobs heterogeneity, this distinction reveals a tradeoff between productivity and adaptability (see Decreuse and Granier (2010)) in schooling choices : while *specific* human capital may be rewarded by high returns in a few specific tasks, *general* human capital may give workers more job opportunities.

To take into account this distinction between human capitals, we build a dynamic discrete choice model *à la* Keane and Wolpin (1997) allowing for heterogeneity in returns to human capital. We then distinguish between general and specialized human capital accumulation during schooling and match diplomas with specific jobs or tasks. With this model, we can identify heterogeneity in labor market returns of education and assess the impact of policies like a modification in the distribution of specialization costs during schooling.

To estimate the model, we use French panel data *Génération 98* , with more than 6500 men over 7 years. All these individuals exit school in 1998 and are interviewed in three waves : 2001, 2003 and 2005. The data provide very detailed individual on both schooling and working trajectories.

Keywords: Schooling Decisions, Dynamic Discrete Choices Model, Specialization, Human Capital.

JEL Classification Numbers:

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Introduction

Schooling choices has at least two distinct dimensions : a vertical one with the number of years and an horizontal one with specialization, or choice of diploma's domain. This paper studies the consequences of adding specialization schooling choices in a dynamic discrete choice model in term of job market outcomes. From a theoretical point of view, human capital can be split in two parts : a general part and a specific one. With the same number of schooling years, a general diploma may give more opportunities in the job market than a job-specific diploma. But a specialized degree can lead to better offers and higher wages. This is a consequence of the arbitrage between adaptability and productivity of individual skills. Decreuse and Granier (2010) show that labor market institutions can increase frictions and then motivates people to acquire general skills. But they also decrease the match surplus raising returns of specialized schooling.

In this paper, we define "specialized" human capital as schooling skills corresponding to daily tasks in the labor market, gathered in group of similar activities. The idea behind that is that we try to link schooling skills with working tasks. Yet, we will need to match diplomas with particular family of jobs for which individuals are trained for. This crucial step will be detailed below in the description of data. As of now, we will use the term "family of jobs" for the group of occupations (activities) corresponding to a specialized degree and we will name this group as "specific" for the individual. In our framework and for the sake of simplicity, we only look at initial schooling and the last obtained diploma. Our data allows us to follow individuals in the labor market at the end of school.

Furthermore, the choice between these two types of schooling is also a question of risk exposition. If specialized, individuals are more affected by shocks in their specific jobs' family and then face this particular risk more than other. In the opposite, the general human capital can help to protect oneself from occupation-specific risk. Intuitively, one can link this with the job-search literature in taking into account the probability of receiving a job offer and the risk for a position to be destroyed.

Our work wants to evaluate if specialized individuals have more difficulties to enter the labor market and what are the gains/losses to work in one specific sector. One can investigate other empirical implications of the theory. For instance, one can think that specialized human capital has bigger depreciation rate. Malamud (2010) develops a model with choices about academic specialization in higher education (with switching) and noisy signals about matches in specific fields. Testing his predictions on British data, he finds evidence that individuals who switch to unrelated occupations initially earn lower wages. Although more switching occurs in England where students specialize early, higher wage growth among those who switch eliminates the wage difference after several years.

Our idea is then to consider wage differences between jobs according to family-specific returns to schooling. While considering differences between number of years of schooling, it is then possible to consider differences between domain or speciality and thus in the specialization of schooling choices. As said before, this is based on the theoretical arbitrage between productivity and adaptability in the labor market. The simple idea of our model will be that we want to have more dimensions in the basic Mincer-equation model of human capital[1] : first, in the labor market with occupation-specific returns of education and second in schooling choices while matching some diplomas with corresponding jobs.

Buchinsky, Mezza, and McKee (2010) estimate a structural dynamic programming model à la Keane and Wolpin (1997) introducing the two types of schooling (general and specific) and allowing to work while at school. Using 16 occupation-industry employment combinations, the preliminary results show that these two types of educational choices have huge impact on career paths and occupational choices.

[1]Strictly speaking, we do not use the optimal stopping framework and will consider the dynamic aspect of choices as crucial.

In a similar framework, Adda, Dustmann, Meghir, and Robin (2010) compare apprenticeship system in Germany showing that apprentices and non-apprentices have different wage and job dynamics. In particular, apprentices face higher wage increase at the beginning of their career and do not seem to suffer from job reallocation. On the other hand, non-apprentices face higher wage heterogeneity and higher returns from job search.

This paper is organized as follows. The next section gives a basic structural model and the following presents the data. Then, Section 4 discusses the identification strategy and estimation method. Section 5 analyzes the empirical results. Extensions and concluding remarks are offered in the two last sections.

1 Model

The model is divided into two parts. First, individual make sequential schooling decisions choosing an optimal level of schooling[2]. Optimality is defined in terms of the job market value of the schooling level. Thus, when the schooling track is finished, individual enter the labor market and make occupational choices. When entering the labor market, they choose their speciality $v \in \{1, \ldots, V\}$ and then can work in different occupations or be unemployed. We let the available specialities depend on the schooling level $d : v \in \mathcal{V}_d$. Furthermore, to reduce the state space dimension, we suppose that when this speciality is chosen, it remains unchanged.s

If we note β the discount factor, Ω_t the state space at time t, including state variables and random draws, and d_t^k an indicator variable for choice k at time t, the general Bellman

[2]Because some level last more than one year, it is not equal to the number of years schooling but it is closely related. The correspondence is given in the data section. In our model, this particular aspect will be captured by specific differences in the utility function (schooling costs).

equations are :

$$V_t(\Omega_t) = \max_{1\leq i\leq K} V_t^i(\Omega_t)$$
$$V_t^k(\Omega_t) = u_t^k + \beta\mathbb{E}[V_{t+1}(\Omega_{t+1})|d_t^k = 1, \Omega_t]$$

To avoid notation burden, we will forget to write the conditioning in the $\mathbb{E}\max$ term. The set Ω_t can be written in three parts : choice variables at time t, ω_t and random draws at time t, $\overline{\omega_t}$ and past state space, given initial characteristics Ω_0 : $\Omega_t = \Omega_{t-1} \cup \omega_t \cup \overline{\omega_t}$.

In this section, we write value functions at time t of some choice k conditional on being in state ω_t : for schooling, it will be noted $V_t^{S,k}(\Omega_t)$ and $V_t^{L,k}(\Omega_t)$ for the labor market. We then give the precise timing of our model.

1.1 Schooling decision

1.1.1 Level Choice : length of schooling

Schooling track is sequential and designed into D levels : at each level d, individual have the possibility to leave school and enter labor market or to continue at school to the next schooling level. Given the complexity of schooling trajectories, several choices are available at each node. At node d, we denote $\mathcal{S}_d$ available schooling levels and $\mathcal{V}_d$ available job market alternatives, so that choices for each schooling level are noted $\mathcal{C}_d = \mathcal{S}_d \cup \mathcal{V}_d$. Level D is the last available schooling level after which people can only enter the labor market.

Transition cost from level d to level d' is denoted by $c_d^{d'}(Z, \kappa_d^{d'})$ where Z is a vector of individual covariates influencing schooling decisions and $\kappa_d^{d'}$ is a random shock. One will add a supplementary linearity assumption for these costs : $c_d^{d'}(Z, \kappa_d^{d'}) = \alpha_d^{d'} + Z'\gamma_d + \kappa_d^{d'}$.

The schooling levels have different time length, the basic period is monthly in our model, we note $l_d^{d'}$ the time in month to end schooling level d' if level d completed. For $1 < d < D$, conditional on being at state d, the value function of choice $k \in \mathcal{C}_d$ at time t is[3] :

$$V_t^{S,k}(\Omega_0 = Z, \omega_t = d, \overline{\omega_t} = \kappa_d^k) = c_d^k(Z, \kappa_d^k) + \beta^{l_d^k}\mathbb{E}[\max_{l \in \mathcal{C}_d} V_{t+1}^l(\Omega_{t+1})]$$

where V_{t+1}^l can be value functions for schooling $V_{t+1}^{S,l}$ or working $V_{t+1}^{L,l}$, defined below; the expectation is taken on future realizations of random draws (the exact timing will be detailed below).

1.1.2 Job Market Alternatives

At the end of each level of schooling, individuals can choose to enter labor market. As said in the introduction, we define a occupation as a set of jobs corresponding to some specific schooling specialization. The value of working will then depend on the type of occupation to which individuals choose to specialize. According to our specific data set, we suppose that it is impossible to come back to school (we actually observe less than 1% of monthly individuals trajectories returning to school).

Conditionally on some unobserved heterogeneity, labor market choices[4] are made in a job search framework according to the labor market value of schooling levels cross occupations. Labor market value functions of speciality $k \in \mathcal{V}_d$ given schooling d and characteristics Z

[3] In the extended version of the model, we will add a probability of failure in the schooling process to take into account some non chosen drop out.

[4] Strictly speaking, we first consider job market alternatives as a schooling specialization at the end of schooling initial track, meaning the specific occupation and then as employment/unemployment job search model.

are:

$$
\begin{aligned}
V_t^{S,k}(\Omega_0 = Z, \omega_t = d, \overline{\omega_t} = \eta^k) &= Z'\gamma_k + \eta^k + p_t^k \cdot V_t^E(\varepsilon^k) + (1 - p_t^k) \cdot V_t^U \\
V_t^E(\varepsilon^k) &= R_t^{E,k}(\varepsilon^k) + \beta\{\lambda_1^k \mathbb{E}[\max(V_{t+1}^E(\varepsilon^k), V_{t+1}^E(\varepsilon^{*k}))] \\
&\quad + \delta^k V_{t+1}^U + (1 - \lambda_1^k - \delta^k) V_{t+1}^E(\varepsilon^k)\} \\
V_t^U &= R_t^U + \beta\{\lambda_0^k \mathbb{E}[\max(V_{t+1}^E(\varepsilon^{*k}), V_{t+1}^U)] + (1 - \lambda_0^k) V_{t+1}^U\}
\end{aligned}
$$

where $\eta = (\eta^1, \dots, \eta^V)'$ a random vector of unobserved tastes (or costs) for occupations, it can be interpreted as comparative advantages in productivity and supposed to be known by individuals. $V_t^E(\varepsilon^k)$ is the value of being employed at time t and V_t^U the value of being unemployed at time t (explicit expressions of reward functions $R_t^{E,k}(.)$ and R_t^U are given below). Conditionally of having a speciality k, λ_0^k is the probability to receive a job offer if unemployed, λ_1^k is the probability to receive an outside job offer if employed and δ^k is probability of a matching destruction (all taken as exogenous). According to our two steps model, we suppose that when individuals leave schools, they do not have automatically a job offer and then can be unemployed : we introduce a Bernoulli random variable $p^k \sim \mathcal{B}(\lambda_0^k)$ giving the probability to have an offer while leaving school with speciality k (realizations are indexed by t). Because of the job search structure, ε^k is a job specific random variable : a draw is done at the beginning of each job and keep constant until leaving position ; ε^{*k} are new draws for outside options[5]. We suppose no randomness in the rewards of unemployment.

Finally there are as many job market alternatives as there are available specialities and individuals take these into account in their schooling decisions. We make the implicit and strong assumption that tastes influence schooling specialization choices but does not play any role in the job market utility.

[5] We do not index the ε's by t because realizations only change when entering a new job.

1.2 Timing and Labor Market Dynamic

The labor market dynamic correspond to a simple job search model with on the job search. We first include only two states : employed or unemployed (E and U). Time is indexed by subscript t and T is time horizon[6]. We note labor market experience in the labor market X_t : the evolution of this state vector is $X_{t+1} = X_t + d_t^E$ where d_t^E is the choice dummy for employment.

All individuals are in school at period 1. The speciality k is determined during the transition to the labor market and then we let it fixed. Conditionally on being in level d, the schooling timing is the following:

1. At each period t, individuals have job offers in each occupation set $v \in \mathcal{V}_d$ if $p_t^v = 1$ (realization of a random variable $p^k \sim \mathcal{B}(\lambda_0^k)$) and they also draw random shocks κ_d^k for $k \in \mathcal{S}_d$ (schooling costs).

2. If they find an offer in speciality v, they draw a realization of ε^{*v} (random part of wage).

3. They make a decision according to the maximization of value functions, i.e. comparing $V_t^{S,k}$ and $V_t^{L,v}$.

4. And then move to the next period.

After entering the labor market, speciality v remains constant and the timing is the following :

1. If they are working (resp. unemployed), they receive outside offers with probability λ_1^v (resp. λ_0^v) and probability of destruction is δ^v.

2. If they have an offer, they draw a realization of ε^{*v} (random part of wage).

[6] One can also imagine that T_d is specific to the final schooling level (d).

3. They make a decision according to the maximization of value functions, i.e. comparing V_t^U and V_t^E.

4. And then move to the next period.

The reward functions of employment and unemployment are for schooling level d:

$$\begin{aligned} R_t^{E,k}(\varepsilon^k) &= f_k(s, X_t) \times e^{\varepsilon^k} \\ R_t^U &= b_u \end{aligned}$$

where s is the actual number of years of schooling (deterministic transformation of d), $\varepsilon^{*k} \sim \mathcal{N}(0, \sigma_k)$ is the job specific random draw, b_u is unemployment benefit or home production, f_k is a Mincer equation with a constant depends on speciality k :

$$f_k(s, X_t) = e^{\alpha_0^k + \alpha_1^k X_t + \alpha_2^k X_t^2 + \alpha_3^k s}$$

1.3 Matching diplomas and jobs

One first way to improve our model is to take into account wether individuals work in jobs corresponding to their diplomas or not. We call "specific" jobs as those related to the speciality at the end of studies. So, once they start their career, individuals face a two groups of opportunities in the labor market : one with the set of jobs corresponding to their degree and another, called "general", with all occupations not related to their schooling specialization.

We construct a many-to-many correspondence between diplomas and jobs and it is explained in the data section how we create this matching table between occupations and schooling speciality. The basic idea is that each schooling specialization is related to a set of jobs[7]. This relation is based on what individuals learn at school and how their future work is linked to this. The principle behind that is to create for each employement spell a binary indicator equalling 1 when the individual work in an occupation corresponding to her speciality (meaning the related set of jobs). Therefore, the working population of each schooling speciality is split in two distinct groups : those who works in the "sector" of linked occupations (and then accumulate some sort of specific experience) and those who works in the general occupations with respect to their schooling specialization.

We then define a specific experience Y_t for each individual as the number of worked months in the set of jobs related to the individual schooling speciality[8]. Recall that the speciality remains fixed in the labor market for each individuals because we suppose that a specialization is occupation specific.

We add this aspect in the model in distinguishing specific or general reward functions $R_t^{E_g}$ for the general family of jobs and $R_t^{E_v}$ for the set of occupations corresponding to the individual speciality v[9] :

$$
\begin{aligned}
f^g(s, X_t) &= e^{\alpha_0^g+\alpha_1^g X_t+\alpha_2^g X_t^2+\alpha_3^g s} \\
f^v(s, X_t, Y_t) &= e^{\alpha_0^v+\alpha_1^v X_t+\alpha_2^v X_t^2+\alpha_3^v s+\alpha_4^v Y_t+\alpha_5^v Y_t^2}
\end{aligned}
$$

We underline that the parameters α_i^g are common to all individuals and the parameters α_i^v are for those who completed with speciality v.

Timing is similar than the previous one, but individuals have more possibilities of jobs because they receive offers from the other "sector" with probabilities λ_i^g or λ_i^v, $i \in \{0;1\}$.

[7] This set can be empty if the degree is *general*.

[8] It can be noted Y_t^v if individual has speciality $v \in \mathcal{V}_d$ but we prefer not writing the superscript because v is fixed for each person in the labor market.

[9] With V specialities, we have $V+1$ functions but individuals only face two : the one of her speciality f^v and the general one f^g.

Labor market values have then similar forms for individuals with speciality $k \in \mathcal{V}_d$:

$$\begin{aligned}
V_t^{E_k}(\varepsilon^k) &= R_t^{E_k}(\varepsilon^k) + \beta\{\lambda_1^k \mathbb{E}[\max(V_{t+1}^{E_k}(\varepsilon^k), V_{t+1}^{E_k}(\varepsilon^{*k}))] \\
&\quad + \lambda_1^g \mathbb{E}[\max(V_{t+1}^{E_k}(\varepsilon^k), V_{t+1}^{E_g}(\varepsilon^{*k}))] \\
&\quad + \delta^k V_{t+1}^U + (1 - \lambda_1^k - \lambda_1^g - \delta^k) V_{t+1}^{E_k}(\varepsilon^k)\} \\
V_t^{E_g}(\varepsilon^k) &= R_t^{E_g}(\varepsilon^k) + \beta\{\lambda_1^g \mathbb{E}[\max(V_{t+1}^{E_g}(\varepsilon^k), V_{t+1}^{E_g}\varepsilon^{*k}))] \\
&\quad + \lambda_1^k \mathbb{E}[\max(V_{t+1}^{E_g}(\varepsilon^k), V_{t+1}^{E_k}(\varepsilon^{*k}))] \\
&\quad + \delta^k V_{t+1}^U + (1 - \lambda_1^g - \lambda_1^k - \delta^k) V_{t+1}^{E_g}(\varepsilon^k)\} \\
V_t^u &= b_u + \beta\{\lambda_0^k \mathbb{E}[\max(V_{t+1}^{E_k}(\varepsilon^{*k}), V_{t+1}^U)] \\
&\quad + \lambda_0^g \mathbb{E}[\max(V_{t+1}^{E_g}(\varepsilon^{*k}), V_{t+1}^U)] + (1 - \lambda_0^k - \lambda_0^g) V_{t+1}^U\}
\end{aligned}$$

1.4 Identification Issues

[Discussion on the λ^k taken as exogenous]

2 Data

2.1 The *Génération 98* Panel Data

The *Génération 98* survey is a representative survey of 16 000 young people leaving the French schooling system for the first time in 1998. This large scale survey is conducted by Céreq[10]. People returning to school during the first year are not considered by the survey. After leaving school, individuals are followed during 7 years reporting the different steps of their working career during three retrospective interviews in 2001, 2003 and 2005[11].

[10] French Center for Research on Education, Training and Employment.

[11] About 742 000 individuals left the schooling system in France in 1998. In the first wave in 2001, 54 000 young people were interviewed from whom 33 000 were selected to enter the panel data. In 2003, 22 000 out of the 33 000 were asked and at the end, about 16 000 individuals are in the selected subsample of whole data set. If we look at the probability to be surveyed at the three dates, there are less unemployed, more

Génération 98 has thus the particular advantage to document many aspects of early labor market transitions and contains individuals facing the same labor market conditions after 1998.

During the first interview, individuals detailed their education trajectory which allow us to rebuild the path of their schooling decisions. To have a realistic approach of schooling decisions, we choose to model decisions at several key moments of schooling trajectories when individuals obtain a qualification that may be valued on the labor market.

We then define 6 nodes at which people make decisions. These levels of schooling are the following:

- $d = 1$: End of 9^{th} grade most of children have age 16 which corresponds to the maximum of compulsory age of schooling in France.
- $d = 2$: Short professional track that ended with a qualification (*BEP/CAP*)
- $d = 3$: High-school diploma (*baccalauréat*)
- $d = 4$: Short college track (BTS, DUT)
- $d = 5$: Bachelor degree
- $d = 6$: higher degrees (Master/PhD degree and French *Grandes Écoles*)

Available path between nodes are given by Figure 1. From the first node, there are several path and duration of path may be different. This differentiation only matters for the duration of the labor market career and is captured through the cost of transition from one node to another. Several covariates allow to model cost of schooling. We choose to use grade repetition before grade 6, family background and context variables that proxy for school, institutes and college proximity.

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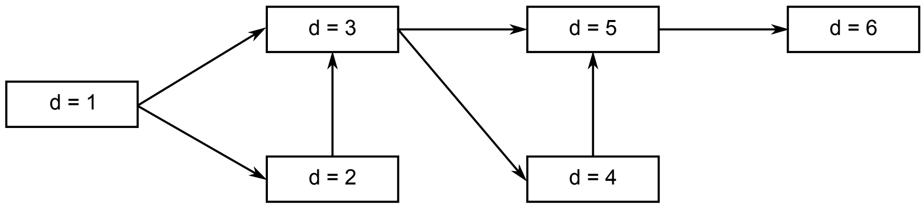
high educated and less living in the Paris region.

Figure 1: French Schooling System (Levels d)



The labor market situation of individuals is reported through a monthly retrospective calendar. The survey provides many details on the job or unemployment spells. Wages, job contracts and working activity is reported at the beginning and at the end of each job spell and if the situation changes during a given spell, the moment of the change is reported in the calendar. Thus, only very long job spells lack of within spell information about wages and working situations. However, this lack may be completed using additional information recorded at each interview. Wages are available at the beginning and at the end of each employment spell, we then use interpolation to predict wages.

To measure the match between occupations and jobs, we use two methods. First, we use an empirical method based on public determining matches according to the composition of workers in terms of specialities (NSF) by type of job (FAP)[12]. A second method consist in using data from institute that advice students about possible professional careers according to the chosen speciality and degree.

2.2 Correspondance between Occupations and Specialization

We explain more precisely in this paragraph how we create the matching table to link each schooling speciality to a set of jobs (i.e. an occupation). The goal is to find an *a priori* on

[12]French acronyms for *Nomenclature des Spécialités de Formation* (Nomenclature of Speciality Training) and *Familles Professionnelles* (Professional Families). With 3 digits, we have about a hundred of specialization, aggregated in 14 specialities with 2 digits. For occupations, we have about 250 distinct families of jobs with 3 digits and 84 with 2 digits.

how diploma should match with occupations.

We can distinguish two ways of matching specialities and jobs :

1. *Statistical* approach: We use the distribution of specialities among occupations according to the official statistics of French Ministry of Labor. For each family of jobs, we know the frequencies of individuals across specialization. Thus, we claim that an occupation corresponds to a schooling speciality if more than 20 % of people working in that occupation are proceeding from this speciality.[13]

2. *A priori* approach: We use actual correspondences given by institutes (such as career job advisors respectively for students and unemployed). This method is closer to an expert approach and intuitively an occupation corresponds to a speciality if they share a set of common skills. Theses tables give for each schooling speciality the set of occupations for which degrees are designed for. And this is the closest to what students actually know and expect : this helps us to capture the informations the students have about this matching. Furthermore, this is also used by unemployed individuals seeking for a job. [**Not currently implemented**]

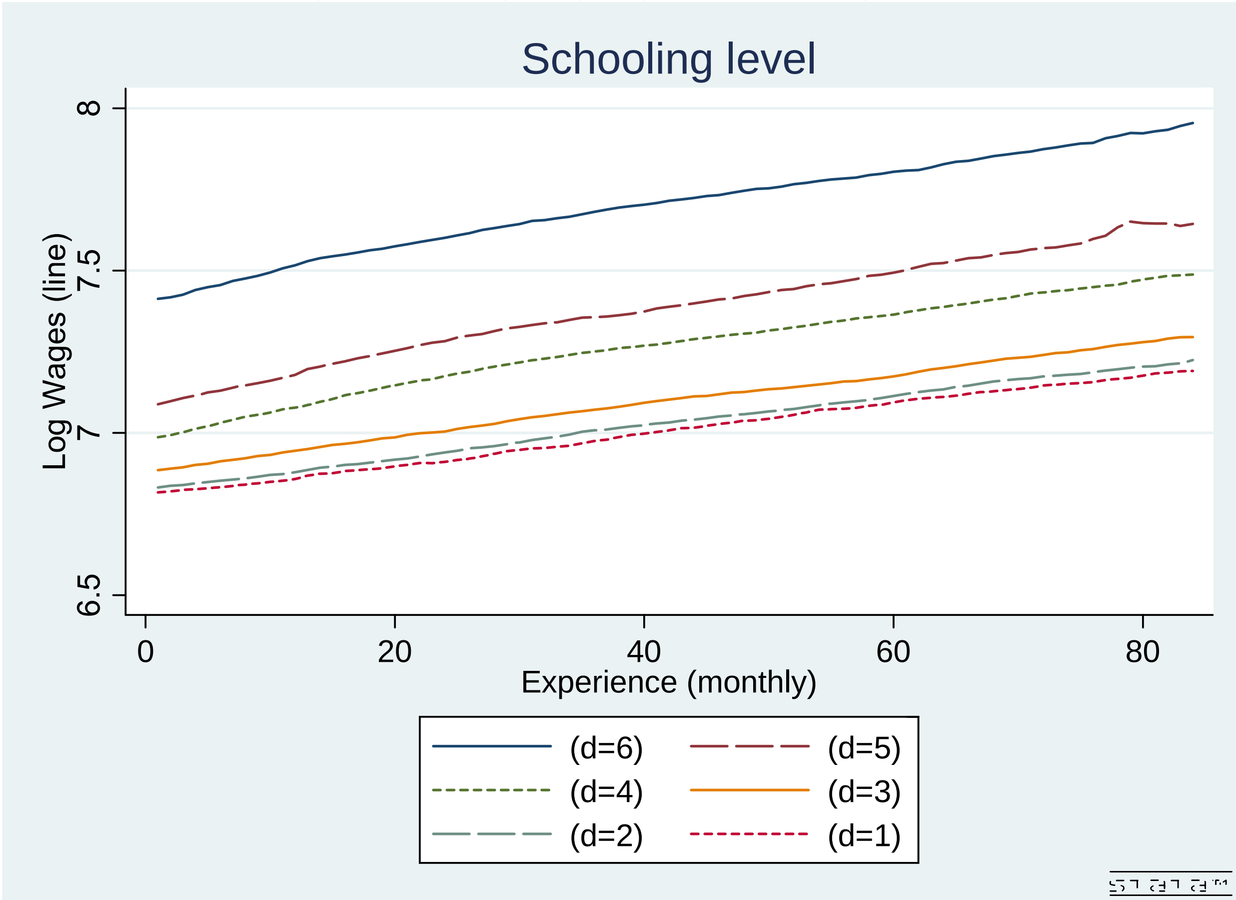
With these two methods, each speciality is match to a set of occupations (potentially empty if the degree is general and so non specialized). We use these two aspects as robustness checks for our results and because both have advantages and disadvantages.

2.3 Descriptive Analysis

This section gives some characteristics of our final sample. In a first basic step and for the sake of simplicity, we keep only male with full-time jobs if employed and consider inactivity

[13]This 20 % seems arbitrary but we checked in depth that the correspondance in not in contradiction to what a naive approach can do, meaning that actual jobs are close to these degrees. Furthermore, 20 % is very often a step value in these distributions. Finally, for a huge majority of occupations, the fifth speciality represents less than 5 % in the population and 20 % = $\frac{1}{5}$ is simply the hypothesis of an uniform distribution between these first five specialities.

Figure 2: Average Log wages and schooling levels



as unemployment. In further work, we will add partial employment offers and inactivity status in our framework. We exclude women of our sample because we do not model fertility choices and it would clearly be something necessary for young individuals in the seven-year period after leaving schooling.

At the end of the day, we have 6568 men with monthly status between 1998 and 2005. It represents 579 040 different sequences[14].

[14]A sequence can last more than a month : individuals change sequence when they change their status (employment, unemployment, etc.).

Figure 3: Job-diploma matches and Wage trajectories by speciality

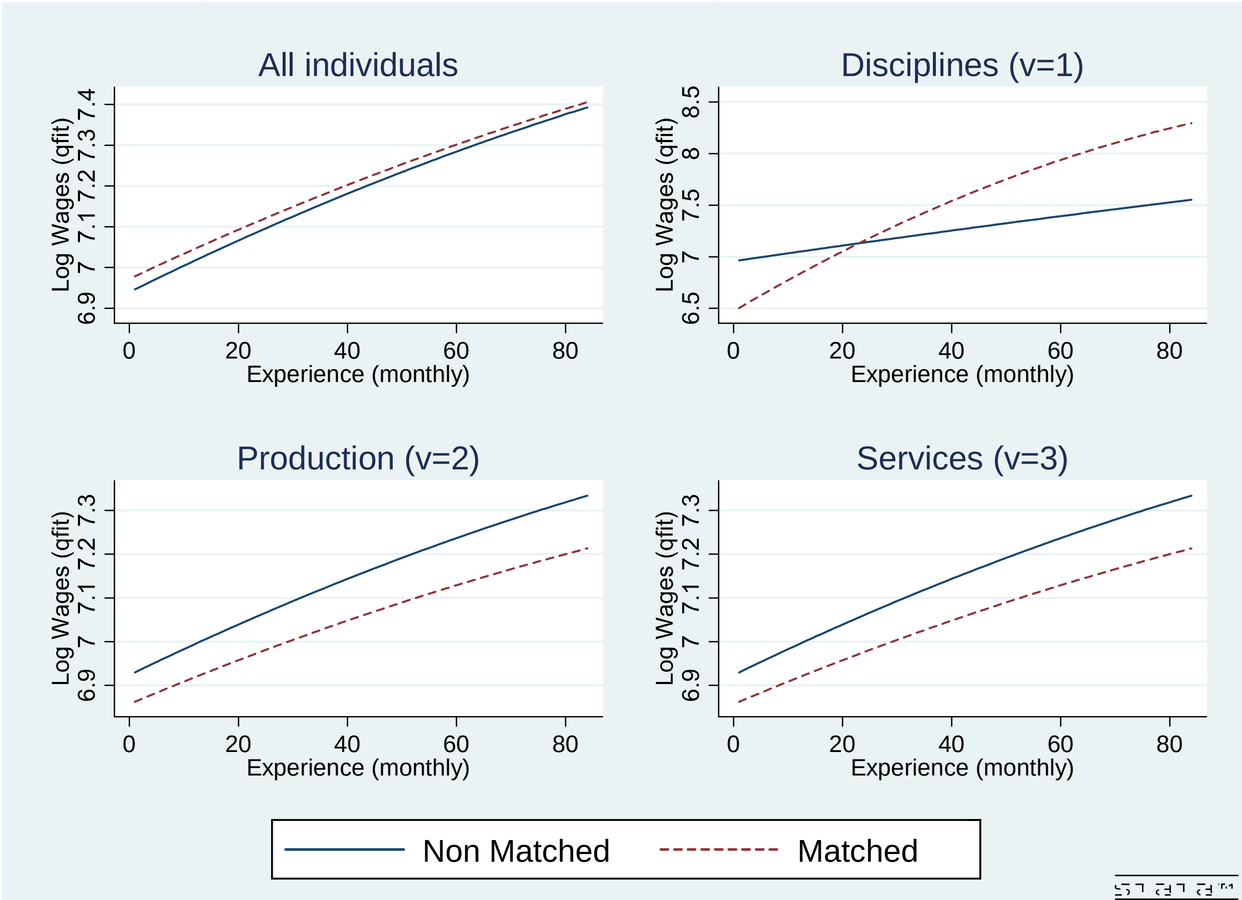
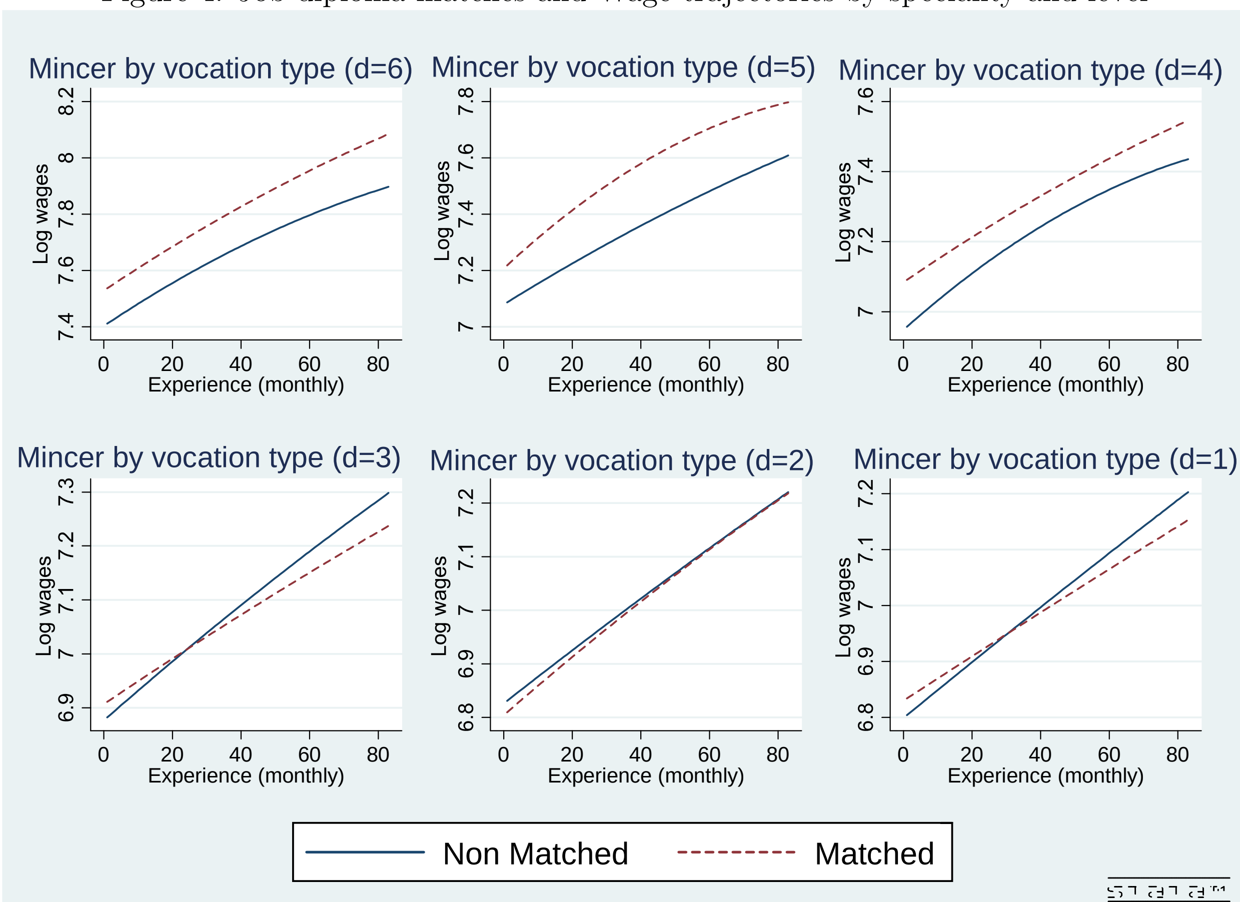


Table 1: **Job-diploma matches**

	Freq.	**Percent**	**Cum.**
Non matched	403,134	81.26	81.26
Matched	92,954	18.74	100.00
Total	496,088	100.00	

Speciality	**Matches' Share**
Disciplines ($v = 1$)	.0035377
Production ($v = 2$)	.166083
Services ($v = 3$)	.3190221
Total	.184271

Figure 4: Job-diploma matches and Wage trajectories by speciality and level



Graphical analysis from Figures 2, 3 and 4 show the differences in wage profile patterns that exist in the two dimensions of schooling. As shown by Figure 1, the vertical dimension of schooling (duration of schooling) has a constant impact on wage profiles, all average wage trajectories being parallel.

On the contrary, Figure 3 show the importance to take into account for speciality since wage profiles are very heterogenous on this horizontal dimension. In the above left corner, we decompose degrees into three categories of speciality, Figure 3 shows that returns from experience are much higher when individual have a degree related to "discipline" jobs[15]. Returns to experience are also slightly higher for degrees specialized in "services" than for degrees specialized in "production". Taking into account more precise categories of speciality in the three other panels (Specialities are divided in 14 categories) shows a much more complex reality. Returns to degrees and returns to experience are on average very different from one speciality to another.

Figure 4 controls simultaneously for the two dimensions of schooling. Heterogeneity among specialities differs according to the number of years of schooling and for a given speciality, wage profile may differ a lot from one schooling level to another. For the highest level of schooling, it seems that there is a wage premium of working in occupations for what you are trained for. This has to be taken with care due to the fact that sample sizes differ between level-cross-speciality groups (Table **??**).

3 Estimations

This section presents our estimation strategies and comments our main results. The first part is dedicated to linear panel data estimations as benchmark for the dynamic programming model in the second part.

[15] University diplomas, engineers schools, etc. It is schooling which is more oriented towards scientific (or academic) knowledge rather than professional techniques.

3.1 Reduced Form

Before estimating our structural model, we estimate some reduced forms.

According to the panel structure of our model, we run different sort of Mincer equations. In a first step, the logarithm of monthly income is explained by monthly experience in three kinds of specification :

1. in a individual fixed effects framework (within estimator), with a quadratic term for experience.
2. with schooling variables such as level and specialities while adding orthogonal individual random effects.
3. in splitting the sample in two subpopulations : those who work in a occupation for which they are trained are compared to those who have a job different from their schooling speciality.

The linear panel model can be written :

$$y_{it} = \alpha + \beta_1 X_{it} + \beta_2 X_{it}^2 + u_i + \varepsilon_{it}$$

where y_{it} is the logarithm of monthly income, X_{it} in the accumulated experience (number of worked months since the entry in the labor market), u_i is an individual specific term and ε_{it} is a normally distributed error term.

u_i is differently specified for each type of estimation : u_i is eliminated by differentiating in the within framework. There is thus no schooling variable in the first type of models. In the two others, $u_i = \gamma_1 S_{it} + \gamma_2 N_i t + v_i$ where v_i is a normally distributed random term.

In a basic robustness test, we also include some observed individual characteristics $u_i = \gamma_1 S_{it} + \gamma_2 N_i t + \delta Z_{it} + v_i$ where covariates are : age in 1998, number of repeated grades in primary school, parents' occupations and an indicator of urban area.

Main results tables are in Appendix section B.

These results are in line with what we found previously in the graphical analysis. Returns of experience are greater for those who learned academic disciplines rather than technical techniques (Tables B.1, B.1 on interpolated incomes and B.1, B.1 for observed wages). If we control for level of schooling, this tendency is unchanged (Tables B.1 and B.1).

Furthermore, in the random effect models, returns to schooling are estimated for each level and we observe the same disparities : the job market value of level can be very different across speciality of formation. But this is not clear about how these distinct returns to schooling influence choices. This is how we split the population two part : we distinguish individuals working in occupations corresponding to their degree and people working in jobs not linked with their education's specialization. The corresponding results are in Table B.2. And we use controls in Table B.2.

The next step will be to define a occupation-type specific experience and study its influence on job market outcomes.

3.2 Simulated Method of Moments

Estimation of the model will be obtained through simulated method of moments (see McFadden (1989), Gouriéroux and Monfort (1994)). Although maximum likelihood estimation might be achieved in our case, we chose this method because of the ease of its implementation.

Simulated trajectories are obtained according to the timing described in the model. Given a vector of parameters θ containing all identified parameters of the model, simulated trajectories are used to compute a vector simulated moments $m^s(\theta)$. These moments can be compared to empirical ones $\hat{m}$. Estimators of parameters are then obtained by minimizing the following objective function:

$$(m_s(\theta) - \hat{m})'\Omega^{-1}(m_s(\theta) - \hat{m})$$

where Ω is a weighting matrix that we choose to obtain efficiency (see Gouriéroux, Monfort, and Renault (1996)).

Simulation may also be used to perform conterfactual analysis. Important point of interest would be to estimate welfare gains from changes in schooling costs for individuals.

[**Choice of the moments**]

3.3 Dynamic program and Terminal Values

We solve the dynamic program using the recursive form of the value functions. However, to limit the dimensionality of the problem, we choose to model the terminal period following Keane and Wolpin (2001). Thus, the terminal $\mathbb{E}\text{max}_{T^*}$ function is given as a function of all state variables and choices at time T^*

$$\mathbb{E}\text{max}_{T^*} = \Psi(X_{T^*}, v, d, d_e(T^*))$$

Given that this expected value is equal to the sum of discounted future values of the state in T^*, we choose the following parametric form for Ψ:

$$\Psi(X_{T^*}, v, d, d_e(T^*)) = \sum_{t=T^*}^{T} W_{T^*}(X_{T^*}, v, d, d_e(T^*)) = \frac{1}{1-\beta} W_{T^*}(X_{T^*}, v, d, d_e(T^*))$$

where W_{T^*} is an average value for individual in state (X_{T^*}, v, d) at time T^* and who choose $d_e(T^*)$ that can be approximated by a polynomial of all covariates.

Then the value function of working and unemployment at time T^* are:

$$\begin{aligned} V_t^E(\Omega_{T^*}) &= h_e^v(d, X_{T^*}) + \varepsilon_t^v + \beta[\Psi(X_{T^*}, v, d, d_e(T^*) = 1)] \\ V_t^U(\Omega_{T^*}) &= h_u^v(d, X_{T^*}) + \beta[\Psi(X_{T^*}, v, d, d_e(T^*) = 0)] \end{aligned}$$

[On going work]

4 Extensions

We will study other job market outcomes such as type of job contracts (short- or long-term) and unemployment risks (exposure and duration).

Future work will be to extend our model to take into account a drop out possibilities during school. It will be done introducing probability of success in the schooling trajectory. One can imagine it with an unobserved part of the individual heterogeneity orthogonal with some observed characteristics.

We are also thinking about adding a supplementary state in the job market : we have inactivity status in the dataset and its individual motivation.

We could also decompose trajectories according to national origin.

Concluding Remarks

A Descriptive tables

A.1 Schooling specialities and levels

Table 2: **Level of Schooling**

Level	**Freq.**	**Percent**	**Cum.**
$d = 6$	659	10.03	17.19
$d = 5$	470	7.16	7.16
$d = 4$	1,314	20.01	85.19
$d = 3$	1,839	28.00	45.19
$d = 2$	1,313	19.99	65.18
$d = 1$	973	14.81	100.00
Total	6,568	100.00	

See Figure 1 for definition of d.

Table 3: **Schooling Specialities** (3 categories)

Schooling Speciality	**Freq.**	**Percent**	**Cum.**
Disciplines ($v = 1$)	871	13.26	13.26
Production ($v = 2$)	4,013	61.10	74.36
Services ($v = 3$)	1,684	25.64	100.00
Total	6,568	100.00	

v is the first digit of the NSF
(i.e. schooling specialities - see first column of table 5).

Table 4: **Schooling Specialities** (13 categories)

Schooling Speciality	**Freq.**	**Percent**	**Cum.**
General Education (10)	151	2.30	2.30
Maths and Sciences (11)	274	4.17	6.47
Humanities and Law (12)	347	5.28	11.75
Literature and art (13)	99	1.51	13.26
Technics of production (20)	450	6.85	20.11
Agriculture, Fishing, Forestry (21)	512	7.80	27.91
Processing (22)	662	10.08	37.99
Civil Engineering, Building, Wood (23)	595	9.06	47.05
Mechanics, Electricity, Electronics (25)	1,794	27.31	74.36
Trade and Management (31)	753	11.46	85.83
Communication and information (32)	280	4.26	90.09
Home and caring services (33)	564	8.59	98.68
Public services (34)	87	1.32	100.00
Total	6,568	100.00	

Table 5: **Schooling Specialities Table**

NSF	French Label	Translation
10	Formations générales	General Education
11	Mathématiques et sciences	Maths and Sciences
12	Sciences humaines et droit	Humanities and Law
13	Lettres et arts	Literature and art
20	Spécialités pluritechnologiques de la production	Interdisciplinary technics of production
21	Agriculture, pêche, forêt et espaces verts	Agriculture, Fishing, Forestry
22	Transformations	Processing
23	Génie civil, construction, bois	Civil Engineering, Building, Wood
25	Mécanique, électricité, électronique	Mechanics, Electricity, Electronics
31	Echanges et gestion	Trade and Management
32	Communication et information	Communication and information
33	Services aux personnes	Home and caring services
34	Services à la collectivité	Public services

A.2 Composition of the sample

Table 6: **Father's Occupation in 1998**

Occupation	Freq.	Percent	Cum.
Farmer	422	6.43	6.43
Craftsman, tradesman, company director	705	10.73	17.16
Senior executive, engineer, teacher	1,030	15.68	32.84
Technician, middle manager	622	9.47	42.31
White Collar	1,694	25.79	68.10
Blue Collar	1,588	24.18	92.28
House, missing or deceased	507	7.72	100.00
Total	6,568	100.00	

Table 7: **Mother's Occupation in 1998**

Occupation	**Freq.**	**Percent**	**Cum.**
Farmer	281	4.28	4.28
Craftsman, tradesman, company director	233	3.55	7.83
Senior executive, engineer, teacher	610	9.29	17.11
Technician, middle manager	295	4.49	21.60
White Collar	3,212	48.90	70.51
Blue Collar	788	12.00	82.51
House, missing or deceased	1,149	17.49	100.00
Total	6,568	100.00	

Table 8: **Mean values by Speciality of Schooling**

Schooling Speciality	**Wages**	**Delay**	**Age in 1998**	**Urban**
General Education (10)	858.0	.735	17.3	.82
Maths and Sciences (11)	1337.1	-.036	24.5	.88
Humanities and Law (12)	1103.9	.023	23.9	.89
Literature and art (13)	1010.9	-.02	23.4	.90
Technics of production (20)	1251.0	.093	22.0	.84
Agriculture, Fishing, Forestry (21)	983.4	.337	20.5	.60
Processing (22)	1036.0	.356	20.2	.75
Civil Engineering, Building, Wood (23)	978.8	.527	19.9	.72
Mechanics, Electricity, Electronics (25)	1053.0	.373	20.4	.79
Trade and Management (31)	1150.2	.160	21.7	.84
Communication and information (32)	1236.2	.075	22.6	.87
Home and caring services (33)	1233.8	.124	23.2	.83
Public services (34)	1171.7	.034	22.9	.89
Total (Mean)	1098.5	.267	21.3	.80

Wages are in euros and calculated for first jobs only.

Delay is the number repeated years during primary school.

Urban is the percentage of individuals living in an urban area in 1998.

Table 9: **Frequencies by Specialities cross Diplomas**

Schooling Speciality	$d=6$	$d=5$	$d=4$	$d=3$	$d=2$	$d=1$	Total
General Education (10)	0	0	0	0	9	142	151
Maths and Sciences (11)	100	42	39	90	2	1	274
Humanities and Law (12)	50	108	57	131	0	1	347
Literature and art (13)	7	29	10	53	0	0	99
Technics of production (20)	90	36	189	86	19	30	450
Agriculture, Fishing, Forestry (21)	18	4	95	225	104	66	512
Processing (22)	42	7	89	145	241	138	662
Civil Engineering, Building, Wood (23)	22	4	42	139	241	147	595
Mechanics, Electricity, Electronics (25)	104	17	266	616	474	317	1,794
Trade and Management (31)	111	63	188	215	103	73	753
Communication and information (32)	53	25	109	57	26	10	280
Home and caring services (33)	41	114	208	77	82	42	564
Public services (34)	21	21	22	5	12	6	87
Total	470	659	1,839	1,313	1,314	973	6,568

Table 10: **Matches Frequency by Speciality of Schooling**

Schooling Speciality	**Perc.**	**Freq.**
General Education (10)	0	13370
Maths and Sciences (11)	0	24129
Humanities and Law (12)	.0075188	30772
Literature and art (13)	0	8793
Technics of production (20)	0	39648
Agriculture, Fishing, Forestry (21)	.1255411	45174
Processing (22)	.3636364	58193
Civil Engineering, Building, Wood (23)	.3333333	52384
Mechanics, Electricity, Electronics (25)	.1457286	158464
Trade and Management (31)	.2396166	66449
Communication and information (32)	.4411765	24760
Home and caring services (33)	.5656934	49257
Public services (34)	0	7647
Total	.2219888	579040

A.3 Graphical Analysis

Figure 5: Average Log wages and schooling specialities

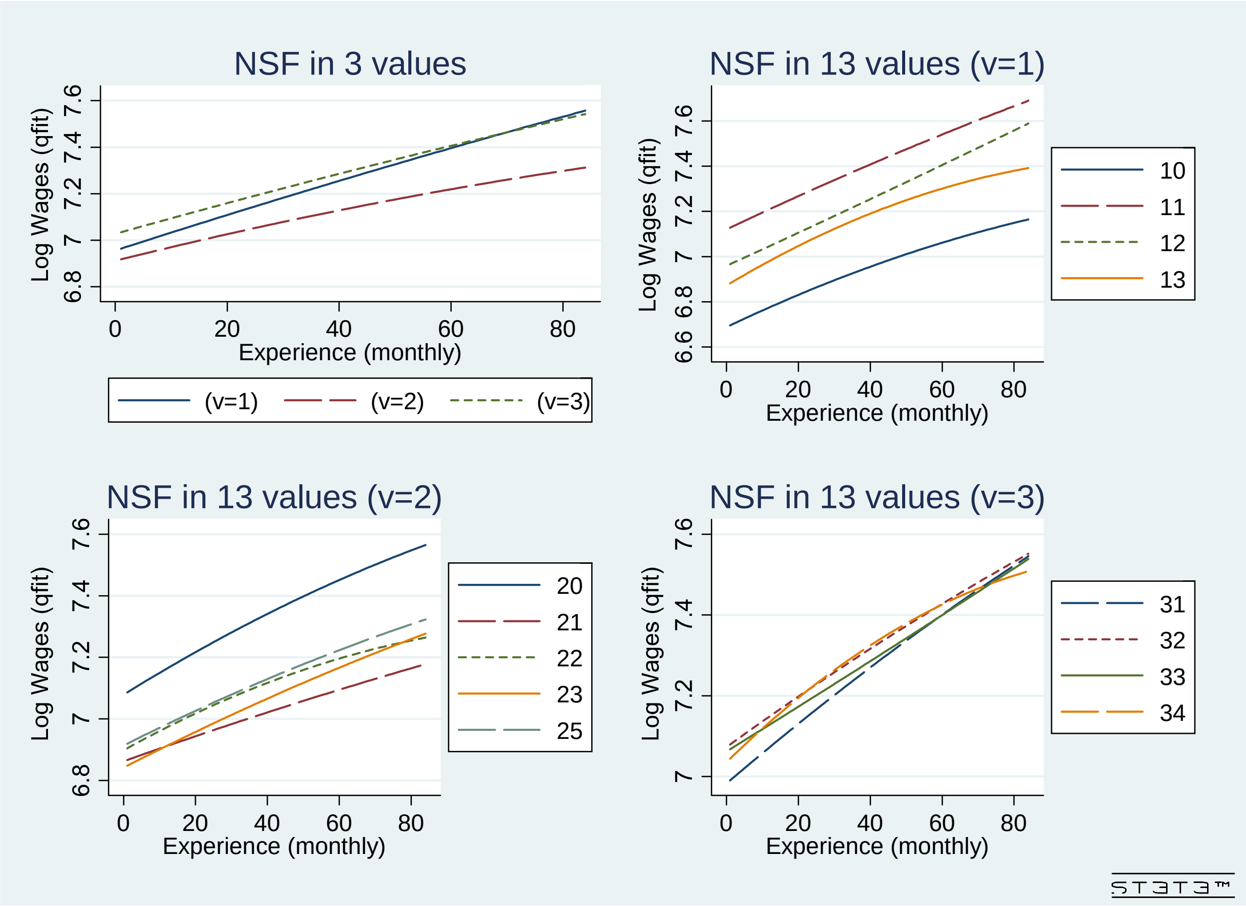


Figure 6: Average Log wages and schooling specialities by level

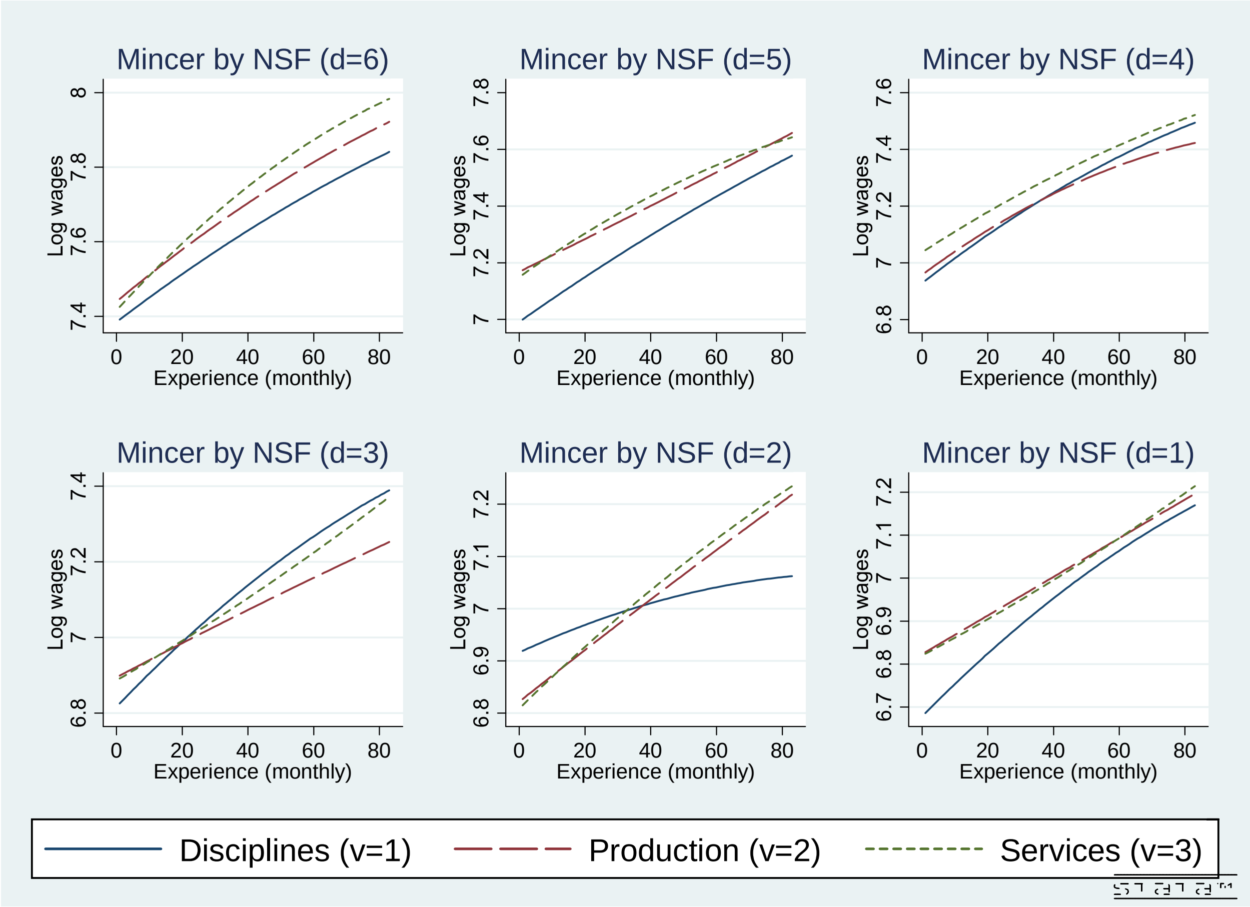
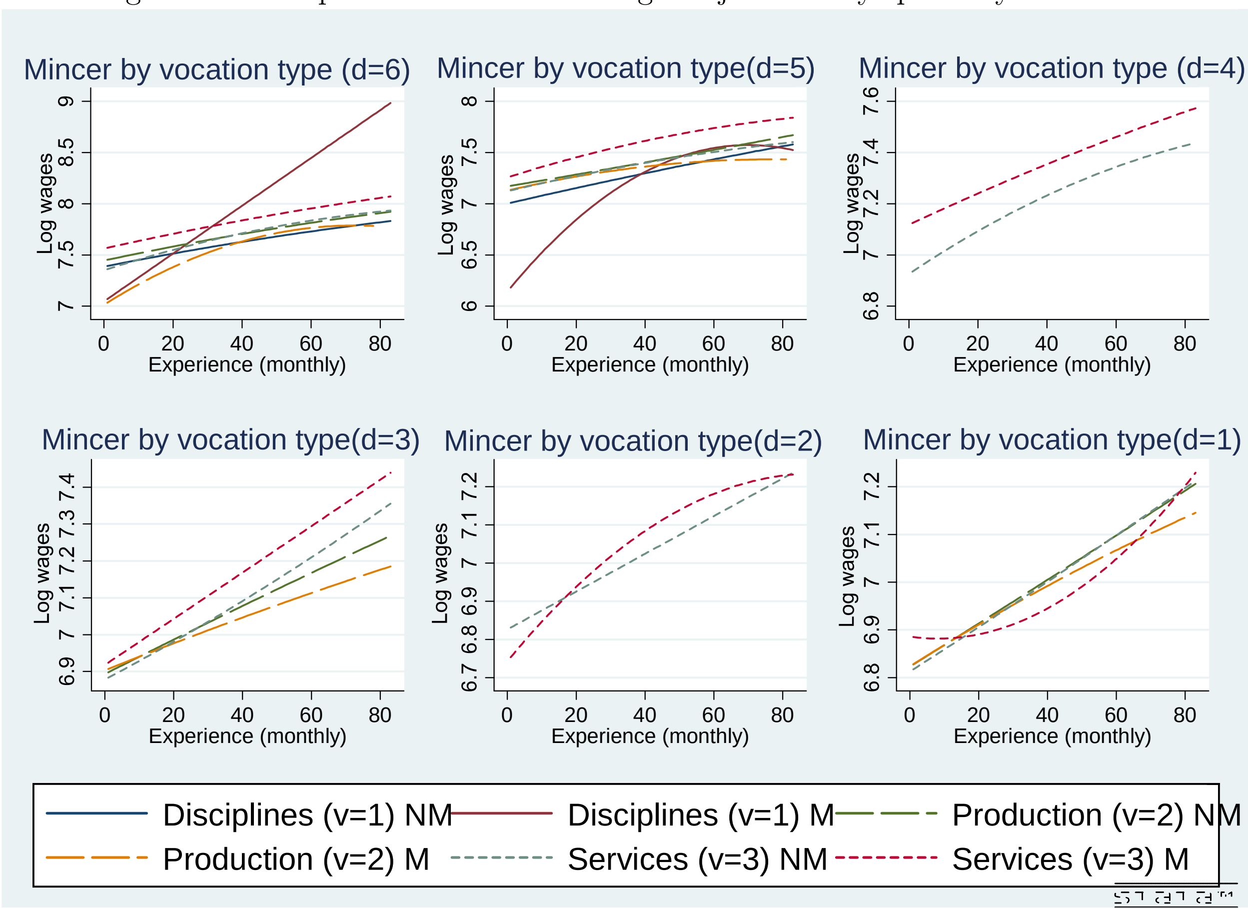


Figure 7: Job-diploma matches and Wage trajectories by speciality and level



B Reduced Form Estimates

B.1 One type of occupations model

Table 11: Individual fixed effects estimation : linear trend

	All	$v = 1$	$v = 2$	$v = 3$
$X_t/100$	.5209***	.6288***	.4832***	.5657***
	(.0057)	(.0172)	(.0071)	(.0112)
cons	6.9684***	6.9978***	6.9263***	7.0552***
	(.0023)	(.0066)	(.0029)	(.0045)
Adj. R^2	.395	.444	.369	.439
No.	496088	60186	308027	127875

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.

Robust standard errors are in parentheses.

Table 12: Individual fixed effects estimation : quadratic trend

	All	$v = 1$	$v = 2$	$v = 3$
$X_t/100$	.6497***	.8676***	.5715 ***	.7238***
	(.0149)	(.0509)	(.0181)	(.0290)
$(X_t/100)^2$	-.1555***	-.2942***	-.1063 ***	-.1911***
	(.0164)	(.0570)	(.0199)	(.0321)
cons	6.9506***	6.9655***	6.9140 ***	7.0333***
	(.0030)	(.0095)	(.0037)	(.0059)
Adj. R^2	.397	.449	.370	.442
No.	496088	60186	308027	127875

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.

Robust standard errors are in parentheses.

Table 13: Random effects model by speciality

	All	$v = 1$	$v = 2$	$v = 3$
$X_t/100$	.6494***	.8673***	.5712***	.7235***
	(.0149)	(.0509)	(.0181)	(.0290)
$(X_t/100)^2$	-.1551***	-.2938***	-.1060***	-.1906***
	(.0164)	(.0570)	(.0199)	(.0321)
$d = 6$	.6830***	.6695***	.6796***	7173***
	(.0117)	(.0277)	(.0138)	(.0262)
$d = 5$	.3585***	.3301***	.3845***	.4137***
	(.0142)	(.0284)	(.0283)	(.0248)
$d = 4$	.2507***	.2885***	.2127***	.2873***
	(.0085)	(.0325)	(.0100)	(.0191)
$d = 3$	.0849***	.1738***	.0600***	.1082***
	(.0078)	(.0246)	(.0087)	(.0205)
$d = 2$	.0202**	.1145	.0067	.0307
	(.0077)	(.0742)	(.0086)	(.0197)
$d = 1$	Ref.	Ref.	Ref.	Ref.
cons	6.7737***	6.6629***	6.8051***	6.7538***
	(.0068)	(.0214)	(.0077)	(.0174)
Adj. R^2	.482	.461	.457	.490
No.	496088	60186	308027	127875

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.

Robust standard errors are in parentheses.

Table 14: Random effects model

	Model 1	Model 2
$X_t/100$	.6494***	.6494***
	(.0149)	(.0149)
$(X_t/100)^2$	-.1551***	-.1551***
	(.0164)	(.0164)
$d = 6$	.6773***	.6830***
	(.0116)	(.0117)
$d = 5$	.3511***	.3585***
	(.0144)	(.0142)
$d = 4$	.2387***	.2507***
	(.0086)	(.0085)
$d = 3$	.0829***	.0849***
	(.0078)	(.0078)
$d = 2$	.0155*	.0202**
	(.0077)	(.0077)
$d = 1$	Ref.	Ref.
$v = 1$	-.0651***	
	(.0107)	
$v = 2$	-.0396***	
	(.0065)	
$v = 3$	Ref.	
cons	6.8115***	6.7737***
	(.0088)	(.0068)
Adj. R^2	.485	.482
No.	496088	496088

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.
Robust standard errors are in parentheses.

Table 15: Individual fixed effects estimation : linear trend (Observed wages)

	All	$v = 1$	$v = 2$	$v = 3$
$X_t/100$	.5262***	.6254***	.4901***	.5718***
	(.0056)	(.0173)	(.0068)	(.0110)
cons	6.9309***	6.9351***	6.8992***	7.0086***
	(.0019)	(.0056)	(.0024)	(.0038)
Adj. R^2	.328	.349	.308	.370
No.	46235	5654	29021	11560

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.
Robust standard errors are in parentheses.
Actual sample is used for this estimation.

Table 16: Individual fixed effects estimation : quadratic trend (Observed wages)

	All	$v = 1$	$v = 2$	$v = 3$
$X_t/100$	.6105***	.7961***	.5400 ***	.6875***
	(.0149)	(.0496)	(.0180)	(.0299)
$(X_t/100)^2$	-.1051***	-.2183***	-.0619 **	-.1440***
	(.0162)	(.0549)	(.0197)	(.0323)
cons	6.9219***	6.9175***	6.8938 ***	6.9963***
	(.0025)	(.0079)	(.0031)	(.0050)
Adj. R^2	.329	.352	.308	.372
No.	46235	5654	29021	11560

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.
Robust standard errors are in parentheses.
Actual sample is used for this estimation.

Table 17: Random effects model by speciality (Observed wages)

	All	$v = 1$	$v = 2$	$v = 3$
$X_t/100$	.6072***	.7859***	.5375***	.6837***
	(.0148)	(.0494)	(.0179)	(.0298)
$(X_t/100)^2$	-.0987***	-.2005***	-.0602**	-.1335***
	(.0163)	(.0553)	(.0197)	(.0323)
$d = 6$	.6710***	.6645***	.6706***	.7013***
	(.0114)	(.0264)	(.0139)	(.0247)
$d = 5$	.3491***	.3245***	.3783***	.4056***
	(.0136)	(.0268)	(.0252)	(.0232)
$d = 4$	.2386***	.2816***	.1966***	.2817***
	(.0081)	(.0316)	(.0095)	(.0177)
$d = 3$	.0824***	.1667***	.0582***	.1084***
	(.0074)	(.0228)	(.0083)	(.0190)
$d = 2$	.0225**	.1072	.0093	.0324
	(.0072)	(.0613)	(.0081)	(.0178)
$d = 1$	Ref.	Ref.	Ref.	Ref.
cons	6.7719***	6.6695***	6.8009***	6.7507***
	(.0063)	(.0197)	(.0072)	(.0158)
Adj. R^2	.437	.444	.410	.457
No.	46235	5654	29021	11560

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.

Robust standard errors are in parentheses.

Actual sample is used for this estimation.

Table 18: Random effects model (Observed wages)

	Model 1	Model 2
$X_t/100$	.6070***	.6072***
	(.0148)	(.0148)
$(X_t/100)^2$	-.0987***	-.0987***
	(.0163)	(.0163)
$d = 6$	.6661***	.6710***
	(.0113)	(.0114)
$d = 5$	.3432***	.3491***
	(.0137)	(.0136)
$d = 4$	.2270***	.2386***
	(.0082)	(.0081)
$d = 3$	.0805***	.0824***
	(.0074)	(.0074)
$d = 2$	.0173*	.0225**
	(.0073)	(.0072)
$d = 1$	Ref.	Ref.
$v = 1$	-.0672***	
	(.0102)	
$v = 2$	-.0373***	
	(.0062)	
$v = 3$	Ref.	
cons	6.8084***	6.7719***
	(.0083)	(.0063)
Adj. R^2	.440	.437
No.	46235	46235

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.
Robust standard errors are in parentheses.
Actual sample is used for this estimation.

	$v = 10$	$v = 11$	$v = 12$	$v = 13$	$v = 20$	$v = 21$	$v = 23$	$v = 25$	$v = 31$	$v = 32$	v
$X_t/100$	.8045***	.8660***	.8344***	1.0681***	.7369***	.4249***	.5530***	.5846***	.5755***	.7986***	.7
	(.1497)	(.0805)	(.0800)	(.1567)	(.0534)	(.0537)	(.0430)	(.0481)	(.0266)	(.0463)	(
$X_t^2/100$	-.2774	-.3666***	-.1698	-.5773***	-.2058***	-.0593	-.1093*	-.0707	-.1067***	-.1939***	-.3
	(.1669)	(.0816)	(.0952)	(.1627)	(.0595)	(.0622)	(.0470)	(.0548)	(.0284)	(.0511)	(
$d = 6$	.0000	.6828***	.4747***	.2795*	.7109***	.5636***	.6557***	.6509***	.6791***	.6850***	.7
	(.)	(.0228)	(.0341)	(.1358)	(.0399)	(.0523)	(.0321)	(.0625)	(.0197)	(.0338)	(
$d = 5$	.0000	.3602***	.1879***	.1235	.3777***	.4873***	.2903***	.4675**	.3811***	.5639***	.4
	(.)	(.0439)	(.0259)	(.0976)	(.0486)	(.1246)	(.0252)	(.1586)	(.0671)	(.0460)	(
$d = 4$	.0000	.3091***	.1404***	.0000	.2504***	.1608***	.2427***	.2214***	.1980***	.2330***	.2
	(.)	(.0351)	(.0376)	(.)	(.0377)	(.0297)	(.0237)	(.0337)	(.0150)	(.0276)	(
$d = 3$	.0000	.1341***	.0485*	.0090	.1577***	.0427	.0690**	.0546**	.0608***	.1160***	.1
	(.)	(.0251)	(.0203)	(.0944)	(.0422)	(.0271)	(.0217)	(.0210)	(.0122)	(.0279)	(
$d = 2$	.1275	.0312	.0000	.0000	.0601	.0393	.0175	.0007	-.0035	.0671*	
	(.0897)	(.0331)	(.)	(.)	(.0456)	(.0313)	(.0182)	(.0182)	(.0125)	(.0274)	(
$d = 1$	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	
_cons	6.6786***	6.7150***	6.7804***	6.8004***	6.7674***	6.7810***	6.8087***	6.7873***	6.8223***	6.7296***	6.7
	(.0321)	(.0164)	(.0147)	(.0807)	(.0381)	(.0258)	(.0176)	(.0161)	(.0113)	(.0239)	(
Adj. R^2	.178	.532	.359	.217	.535	.260	.440	.402	.458	.502	
No.	8397	19530	25623	6636	34491	39713	51174	45547	137102	56310	2

Significativity Levels : * p<0.05, ** p<0.01, *** p<0.001.

Robust standard errors are in parentheses.

Table 19: with controls

	$v = 10$	$v = 11$	$v = 12$	$v = 13$	$v = 20$	$v = 21$	$v = 23$	$v = 25$	$v = 31$	$v = 32$	$v = 3$
$X_t/100$	.8320***	.8864***	.8333***	1.0890***	.7477***	.4195***	.5579***	.5688***	.5728***	.8061***	.7627*
	(.1566)	(.0810)	(.0810)	(.1574)	(.0550)	(.0546)	(.0445)	(.0490)	(.0273)	(.0472)	(.0678
$X_t^2/100$	-.3286	-.3793***	-.1734	-.5972***	-.2250***	-.0567	-.1164*	-.0503	-.1079***	-.2091***	-.3231*
	(.1753)	(.0822)	(.0967)	(.1635)	(.0610)	(.0636)	(.0485)	(.0558)	(.0292)	(.0520)	(.0720
$d = 6$	.0000	.7788***	.4117***	.2930	.6767***	.5859***	.6737***	.6036***	.6 710***	.6608***	.6318*
	(.)	(.1636)	(.1039)	(.1632)	(.0453)	(.0573)	(.0334)	(.0576)	(.0202)	(.0363)	(.0650
$d = 5$	.0000	.4959**	.1418	.1883	.3421***	.4968***	.3176***	.3056***	.3630***	.5701***	.3305*
	(.)	(.1662)	(.1010)	(.1038)	(.0520)	(.1229)	(.0321)	(.0907)	(.0622)	(.0471)	(.073
$d = 4$	.0000	.4839**	.1019	.0000	.2607***	.1455***	.2471***	.2108***	.1875***	.2322***	.2066*
	(.)	(.1666)	(.1002)	(.)	(.0408)	(.0317)	(.0244)	(.0352)	(.0156)	(.0282)	(.060
$d = 3$	.0000	.2777	.0116	.1344	.1689***	.0300	.0828***	.0532**	.0625***	.1303***	.062
	(.)	(.1625)	(.0978)	(.0917)	(.0456)	(.0296)	(.0215)	(.0205)	(.0129)	(.0298)	(.061
$d = 2$	.1707	.2881	.0000	.0000	.0980*	.0346	.0232	.0042	.0028	.0877**	-.052
	(.0891)	(.1746)	(.)	(.)	(.0499)	(.0329)	(.0179)	(.0171)	(.0130)	(.0287)	(.072
$d = 1$	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
_cons	.0000	.0000	.0000	7.0420***	6.6864***	6.7637***	6.8862***	.0000	.0000	6.9501***	.0000
	(.)	(.)	(.)	(.9147)	(.2913)	(.2509)	(.1384)	(.)	(.)	(.2076)	(.)
Adj. R^2	.254	.601	.408	.424	.565	.289	.474	.449	.491	.535	.603
No.	7861	19117	24804	6570	32997	38640	48731	43410	130479	54215	2078

Significativity Levels : * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Robust standard errors are in parentheses.

B.2 Two types of occupations model

Table 20: Random effect model by detailed speciality

	All NM	All M	$v = 1$ NM	$v = 1$ M	$v = 2$ NM	$v = 2$ M	$v = 3$ NM	$v = 3$ M
$X_t/100$	.6497***	.5686***	.8548***	3.3328**	.5794***	.4368***	.6981***	.6958***
	(.0168)	(.0328)	(.0504)	(1.2682)	(.0200)	(.0430)	(.0357)	(.0495)
$(X_t/100)^2$	-.1527***	-.0975**	-.2879***	-1.6348	-.1062***	-.0305	-.1738***	-.1581**
	(.0183)	(.0365)	(.0567)	(1.4714)	(.0218)	(.0488)	(.0390)	(.0547)
$d = 6$	.6666***	.8023***	.6676***	.8293***	.6805***	.5524***	.6733***	.8401***
	(.0119)	(.0379)	(.0277)	(.1667)	(.0141)	(.1039)	(.0282)	(.0556)
$d = 5$	.3409***	.5630***	.3324***	.0000	.3861***	.3507***	.3814***	.6435***
	(.0147)	(.0427)	(.0286)	(.)	(.0285)	(.0885)	(.0260)	(.0581)
$d = 4$	.2148***	.3117***	.2890***	.0000	.2079***	.1933***	.1957***	.3782***
	(.0093)	(.0178)	(.0325)	(.)	(.0106)	(.0239)	(.0219)	(.0440)
$d = 3$	.0861***	.0963***	.1742***	.0000	.0627***	.0709***	.0991***	.2053***
	(.0083)	(.0180)	(.0246)	(.)	(.0094)	(.0188)	(.0213)	(.0508)
$d = 2$	.0230**	.0259	.1146	.0000	.0090	.0189	.0308	.0775
	(.0083)	(.0172)	(.0740)	(.)	(.0093)	(.0185)	(.0207)	(.0488)
$d = 1$	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
cons	6.7731***	6.7719***	6.6659***	6.1823***	6.8032***	6.8104***	6.7581***	6.7067***
	(.0073)	(.0159)	(.0214)	(.0583)	(.0083)	(.0176)	(.0182)	(.0432)
Adj. R^2	.481	.519	.460	.871	.474	.253	.497	.485
No.	403134	92954	59963	223	257055	50972	86116	41759

levels : * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Robust standard errors are in parentheses. “M” (“NM”) for (non) matched jobs-diplomas.

Table 21: Random effect model by detailed speciality (Adding covariates)

	All NM	All M	$v=1$ NM	$v=1$ M	$v=2$ NM	$v=2$ M	$v=3$ NM	$v=3$ M
$X_t/100$	.6497***	.5685***	.8548***	2.2640***	.5795***	.4367***	.6980***	.6958***
	(.0168)	(.0328)	(.0504)	(.1979)	(.0200)	(.0430)	(.0357)	(.0496)
$(X_t/100)^2$	-.1527***	-.0975**	-.2879***	-.3083*	-.1062***	-.0304	-.1737***	-.1581**
	(.0183)	(.0365)	(.0567)	(.1564)	(.0218)	(.0489)	(.0390)	(.0547)
$d=6$	.6527***	.7139***	.6529***	.0000	.6657***	.4954***	.6536***	.8027***
	(.0124)	(.0410)	(.0342)	(.)	(.0143)	(.0948)	(.0286)	(.0567)
$d=5$	.3371***	.4918***	.3270***	-.2951***	.3758***	.3472***	.3723***	.6190***
	(.0151)	(.0435)	(.0325)	(.0159)	(.0277)	(.0908)	(.0270)	(.0599)
$d=3$	.2116***	.2467***	.3002***	.0000	.2062***	.1851***	.1983***	.3532***
	(.0095)	(.0209)	(.0354)	(.)	(.0108)	(.0252)	(.0221)	(.0441)
$d=4$	.0858***	.0865***	.1772***	.0000	.0654***	.0714***	.1027***	.1893***
	(.0083)	(.0184)	(.0283)	(.)	(.0095)	(.0191)	(.0216)	(.0517)
$d=2$	.0238**	.0236	.1094	.0000	.0133	.0179	.0342	.0750
	(.0083)	(.0173)	(.0746)	(.)	(.0092)	(.0178)	(.0211)	(.0485)
$d=1$	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
$v=1$	-.0249*	-.2407						
	(.0110)	(.2227)						
$v=2$	-.0024	-.0889***						
	(.0072)	(.0141)						
$v=3$	Ref.	Ref.						
cons	6.8422***	6.9163***	6.9326***	.0000	6.8244***	6.8073***	6.5800***	6.9883***
	(.0708)	(.1231)	(.2226)	(.)	(.0780)	(.1500)	(.1541)	(.2316)
Adj. R^2	.499	.546	.488	.958	.496	.287	.520	.507
No.	403134	92954	59963	223	257055	50972	86116	41759

levels : * p<0.05, ** p<0.01, *** p<0.001. Robust standard errors are in parentheses. “M” (“NM”) for (non) matched jobs-diplomas. All regression are controlled for region fixed effects, age and parents profession.

Table 22: Returns of schooling by speciality, with matches indicator (Random effects).

	All	All	$v = 1$	$v = 1$	$v = 2$	$v = 2$	$v = 3$	$v = 3$
$X_t/100$	.6517***	.6518***	.8600***	.8600***	.5697***	.5697***	.7382***	.7382***
	(.0152)	(.0152)	(.0518)	(.0518)	(.0185)	(.0185)	(.0297)	(.0297)
$(X_t/100)^2$	-.1587***	-.1588***	-.2831***	-.2831***	-.1042***	-.1043***	-.2120***	-.2120***
	(.0171)	(.0171)	(.0580)	(.0580)	(.0209)	(.0209)	(.0333)	(.0333)
$d = 6$	.6768***	.6572***	.6727***	.6572***	.6780***	.6601***	.7127***	.6831***
	(.0116)	(.0121)	(.0282)	(.0347)	(.0139)	(.0140)	(.0263)	(.0269)
$d = 5$	.3508***	.3385***	.3342***	.3283***	.3826***	.3718***	.4113***	.3918***
	(.0143)	(.0145)	(.0290)	(.0328)	(.0283)	(.0276)	(.0247)	(.0255)
$d = 4$	.2387***	.2347***	.2862***	.2955***	.2121***	.2086***	.2790***	.2703***
	(.0087)	(.0089)	(.0323)	(.0352)	(.0100)	(.0102)	(.0215)	(.0216)
$d = 3$	.0157*	.0194*	.1171	.1091	.0076	.0110	.0286	.0297
	(.0078)	(.0078)	(.0732)	(.0746)	(.0086)	(.0085)	(.0197)	(.0202)
$d = 2$	.0830***	.0818***	.1730***	.1748***	.0611***	.0631***	.1050***	.1009***
	(.0078)	(.0079)	(.0245)	(.0282)	(.0087)	(.0088)	(.0206)	(.0208)
$d = 1$	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
$v = 1$	-.0656***	-.0624***						
	(.0110)	(.0108)						
$v = 2$	-.0393***	-.0387***						
	(.0066)	(.0065)						
$v = 3$	Ref.	Ref.						
ind_spe	-.0026	-.0025	-.3958	-.3936	-.0099	-.0099	.0153	.0152
	(.0093)	(.0093)	(.5513)	(.5517)	(.0100)	(.0100)	(.0199)	(.0199)
_cons	6.8116***	6.8991***	6.6641***	6.9289***	6.8066***	6.8476***	6.7518***	6.7230***
	(.0091)	(.0680)	(.0214)	(.2230)	(.0078)	(.0732)	(.0175)	(.1455)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	.483	.498	.455	.482	.456	.478	.490	.508
No.	484480	484480	58940	58940	300508	300508	125032	125032

Significativity Levels : * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Robust standard errors are in parentheses.

Table 23: Returns of schooling by level, with matches indicator (Random effects).

	All	All	$d=6$	$d=5$	$d=4$	$d=3$	$d=2$	$d=1$
$X_t/100$	.6517***	.6518***	.8500***	.8187***	.8483***	.5525***	.5152***	.5150***
	(.0152)	(.0152)	(.0453)	(.0583)	(.0330)	(.0287)	(.0309)	(.0463)
$(X_t/100)^2$	-.1587***	-.1588***	-.3290***	-.2633***	-.3418***	-.0772*	-.0363	-.0457
	(.0171)	(.0171)	(.0497)	(.0664)	(.0385)	(.0322)	(.0340)	(.0526)
$d=6$	.6824***	.6621***						
	(.0117)	(.0122)						
$d=5$	.3580***	.3456***						
	(.0142)	(.0143)						
$d=4$	.2506***	.2459***						
	(.0087)	(.0089)						
$d=3$	.0850***	.0835***						
	(.0078)	(.0079)						
$d=2$	.0205**	.0235**						
	(.0077)	(.0077)						
$d=1$	.0000	.0000						
	(.)	(.)						
ind_spe	-.0020	-.0019	-.0318	.0282	.0603***	-.0127	-.0378*	.0025
	(.0092)	(.0092)	(.0653)	(.0723)	(.0170)	(.0170)	(.0157)	(.0257)
_cons	6.7738***	6.8694***	7.8407***	7.0623***	7.0609***	7.0451***	6.8211***	6.6044***
	(.0069)	(.0666)	(.3190)	(.3530)	(.1723)	(.1156)	(.1053)	(.1014)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.480	.495	.236	.278	.287	.208	.243	.194
No.	484480	484480	50733	34445	99299	136370	99101	64532

Significativity Levels : * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Robust standard errors are in parentheses.

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