2017/38

DP

Andreu Arenas and Clément Malgouyres

Countercyclical school attainment and intergenerational mobility

CORE
CENTER FOR OPERATIONS RESEARCH AND ECONOMETRICS

CORE
Voie du Roman Pays 34, L1.03.01
Tel (32 10) 47 43 04
Fax (32 10) 47 43 01
Email: immaq-library@uclouvain.be
https://uclouvain.be/en/research-institutes/immaq/core/discussion-papers.html

Countercyclical School Attainment and Intergenerational Mobility*

Andreu Arenas† Clément Malgouyres‡

November 13, 2017

Abstract

We study how economic conditions at the time of choosing post-compulsory education affect intergenerational mobility. Exploiting local variation in birthplace unemployment rate at age 16 across 23 cohorts in France, we find that cohorts deciding on post-compulsory education in bad economic times are more educationally mobile – their level of education is less related to having a white-collar father. These cohorts are also more occupationally mobile; and a large fraction of this effect is explained by business cycle-induced differences in educational attainment. Accounting for differential spatial mobility between birth and age 16 by parental background confirms the results.

JEL codes: J24, I21, E24

Key words: intergenerational mobility, business cycle, human capital, occupational choice

*We are grateful to Samuel Bentolila, Pierre Cahuc, Bart Cockx, Juan Dolado, Bertrand Garbinti, Andrea Ichino, Fabian Lange, Dominik Sachs, Milena Suarez and conference and seminar participants for helpful comments. We also thank INSEE and the Centre Maurice Halbwachs (CMH) for giving us access to the data and for their help. The data used in this paper can be accessed through the CMH.

†CORE, Université catholique de Louvain. Email: andreu.arenasjal@uclouvain.be, Postal address: CORE, Voie du Roman Pays, 34 - L1.03.01 1348 Louvain-la-Neuve, Belgium.

‡Banque de France, LIEPP. Contact: clement.malgouyres@banque-france.fr, Postal address: Banque de France, 49-1374 DGEI-DEMS-SEPS, 75049 Paris Cedex 01 France. The views expressed here are those of the author only and do not necessarily reflect the views of the Banque de France or the Eurosystem.

1 Introduction

Educational choices are endogenous to aggregate economic conditions. Whenever it is more difficult to find a job, the earnings foregone while at school decrease. At the same time, without those earnings, or with reduced parental earnings, it might be more difficult to finance post-compulsory education. Existing evidence for the US, France, and Mexico (Dellas and Sakellaris (2003), Gaini *et al.* (2013), Charles *et al.* (2015), Atkin (2016)) shows that, on average, education is countercyclical, meaning that changes in opportunity costs dominate dominate ability to pay considerations, with cohorts exposed to adverse economic conditions in critical ages obtaining significantly more schooling. However, it is not obvious how the fluctuations in schooling across cohorts induced by the business cycle will be drawn from the parental income distribution. Credit constraints are larger for low-income families, but the change in the optimal level of schooling induced by changes in opportunity costs might be larger for children of low-income families. For instance, this could be due to differences in returns to education by parental background, possibly because of complementarities with earlier investments (Cunha and Heckman (2008), Cunha *et al.* (2010)); or to differences in discount rates (Tanaka *et al.* (2010), Banerjee and Mullainathan (2010)). In addition, the number of students at the margin where economic conditions change the optimal level of schooling might also differ by parental background.[1]

The empirical question we address in this paper is whether the parental background gradient in education significantly differs across cohorts exposed to different conditions at the moment of deciding on schooling; and if it does, whether it translates into long-lasting differences in the parental background gradient in labor market performance. This is an important question for a better understanding of the determinants of intergenerational mobility in income within a society, since skill acquisition is one of the main channels for the transmission of economic advantage across generations (Solon, 1999). Moreover, it provides new insights on the long-run effects of exposure to business cycle fluctuations at critical ages. We address this question using a large sample of labor force survey data on 22 cohorts across 96 French départements (i.e. provinces), exploiting variation in the unemployment rate in the individuals' département of birth at age 16, and information on labor market outcomes, educational attainment, and parental occupation. Crucial in our empirical exercise is the use of local-level variation in economic conditions, allowing us to net out time-specific unobserved heterogeneity, including national trends and policies; the use

[1] Children of rich/white collar parents are more likely to be *always takers*. Findeisen and Sachs (2016) show how the number of students at the margin is a crucial parameter for the effects of financial aid on college enrollment.

of the unemployment rate by département of birth, allowing us to rule out geographical sorting due to economic conditions at the moment of choosing education; and the use of the unemployment rate at the moment of finishing post-compulsory education, allowing us to rule out simultaneity problems between the unemployment rate and the cohort's education decisions.[2] Our measures of schooling attainment are indicators for holding post-compulsory and college degrees. Our measure of labor market outcomes, both for the children and the parents, is binary – white vs. blue collar occupation –, and is strongly correlated with contemporaneous earnings and educational attainment, which we do not observe for parents.

The results indicate that cohorts deciding on post-compulsory education in bad economic times are more educationally mobile, meaning that their educational attainment is less correlated with having a white-collar father. We find an analogous effect in the labor market: these cohorts are also more occupationally mobile, meaning that their probability of obtaining a white-collar job is less correlated with having a white-collar father. We find that a large fraction of this difference in occupational intergenerational mobility is explained by differences in educational attainment, which is consistent with our first finding. Hence, our results suggest that although recessions might tend to increase inequality (Bonhomme and Hospido, 2017), due for instance to the skill-biased nature of unemployment, the lack of labor market alternatives pushes especially the children of the low skilled to obtain more education, resulting in higher intergenerational mobility in education and labor market outcomes within the treated cohorts. The results are robust across a number of specifications, the most demanding one featuring département by year of birth fixed effects, that absorb all unobserved heterogeneity within a cohort in a province, département by parental occupation fixed effects, that absorb all time-invariant unobserved differences between white and blue collars that might systematically change across départements, and département by parental background time trends. Occupational mobility regressions feature additional controls – survey year by birth year fixed effects and age at survey by parental skill fixed effects –, to allow for heterogeneous career profiles by age and parental background (Lee and Solon, 2009). We frame our analysis and interpret the findings using a one-factor model of selection into education where education affects the probability of access to white versus blue-collar occupations and within-occupation earnings. The model allows us the decompose the business cycle implications of occupational mobility into a

[2]The literature using aggregate unemployment is indeed subject to the criticism that national unemployment rate might be correlated with nation-wide reforms. This issue is particularly salient in the French case during the period analyzed, as many of the late 1980s reform to increase educational attainment were decided partly as a reaction of the high unemployment rate among the youth which was in part cyclical (Gaini *et al.*, 2013; Esquieu and Poulet-Coulibando, 2003).

component that is driven by the endogenous responses of educational attainment and a component that reflects changes in occupational mobility due changes in the occupational returns of education. The latter component could potentially be biased students with low parental background, notably if parental networks are more intensively used during period high unemployment years, as shown in Kramarz and Skans (2014), and that white collar parents' networks are more productive. The empirical results presented in the paper show that the former effect is a much more potent force explaining the counter-cyclicality of occupational intergenerational mobility and that the latter effect is not significantly different from zero.

Since we exploit variation based on the unemployment rate at the département of birth, one possible concern is about differential mobility between birth and age 16 (and hence exposure to economic conditions) by parental background. It could be for instance that high parental background students are found to be relatively less responsive to their birthplace's economic conditions simply because they are more likely to have moved and be exposed to different economic conditions at age 16. We account for this possibility by using a Two-Sample 2SLS estimator (Angrist and Krueger, 1992; Inoue and Solon, 2010), finding that it is unlikely to explain our findings, and if anything, it reinforces the results.

Finally, to complement our previous results on educational attainment and labor market outcomes, that use retrospective information on adults older than 25, we use data on current enrollment of young adults in the Labor Force Survey. We provide evidence that students with low-parental background react more strongly to unemployment faced at age 15 or 16 than high-parental background students, but that this gap reverses and changes in sign at age 22. These results are quite intuitive as they suggest that low parental background individuals adjust relatively more through enrollment in post-compulsory education while high parental background students use higher education as a buffer against local economic conditions relatively more.

By identifying a channel through which the transmission of economic advantage fluctuates across cohorts, we contribute to the literature on the determinants of inter-generational mobility within countries - an exercise that is very data demanding (our sample features almost 200.000 adults with retrospective information, more than 20 cohorts across 96 local labour markets). Recent papers have empirically examined the geography of inter-generational mobility (Chetty *et al.*, 2014); its evolution over time (Aaronson and Mazumder, 2008; Lee and Solon, 2009; Güell *et al.*, 2014; Olivetti and Paserman, 2015; Barone and Mocetti, 2016); the role of women's rising labor force participation (Hellerstein and Morrill, 2011); the role of the education system (Oreopoulos and Page, 2006; Pekkarinen *et al.*, 2009); the effect of worker displacement (Oreopoulos *et al.*, 2008); and the correlation of mobility measures with economic and social outcomes (Güell *et al.*, 2015).[3] Our results imply that a cohort exposed to worse economic conditions at age 16 (for instance, to the 75th percentile of the unemployment rate as opposed to 25th percentile) feature an intergenerational elasticity of being employed in a white collar occupation that is 4% lower. This effect is economically significant, but relatively small compared to the effect of a change in the educational system. For instance, Pekkarinen *et al.* (2009) report a 23% reduction in the intergenerational elasticity of income in Finland after a major educational reform that shifted the selection of students to vocational and academic tracks from age 11 to age 16.

Our findings complement an increasing body of evidence highlighting that adverse economic shocks at early stages of individuals' lives can have persistent effects on labor market outcomes, health, fertility, or preferences (e.g. Maclean, 2013; Giuliano and Spilimbergo, 2014; Chabé-Ferret and Gobbi, 2016). Most relevant to us are the well documented wage losses entailed by entering the labor market in a recession (Arulampalam, 2001; Oreopoulos *et al.*, 2012; Altonji *et al.*, 2016; Cockx and Ghirelli, 2016). In this paper, we add to this literature by studying how the exposure to adverse economic conditions at the moment of making educational choices attenuates the role of family background for students' education and labor market outcomes, through its effects on the opportunity costs of schooling, despite its effect on the ability to pay for it. The lack of economic opportunities makes early school leaving less attractive, and prevents a significant fraction of children of low-skilled families from doing it, which makes them more likely to obtain additional qualifications and eventually a white collar job.

Our paper is also closely related to existing contributions analysing the effects of the business cycle on education (Betts and McFarland (1995), Dellas and Sakellaris (2003), Black *et al.* (2005), Méndez and Sepúlveda (2012), Gaini *et al.* (2013), Charles *et al.* (2015), Aparicio-Fenoll (2016), Atkin (2016), Maier and Vujić (2017)). The main contribution of our paper is that it focuses on differences by parental background and on long-run outcomes in the labor market, while these analysis are generally restricted to enrollment or more rarely educational attainment. The closest papers to ours are Gaini *et al.* (2013), that study school-leaving decisions in France as a function of the national business cycle, finding that they are mostly driven by students of worse social background; and Charles *et al.* (2015), Atkin (2016), which exploit the US housing boom and Mexico's trade reforms, respectively, to show that good economic conditions at the local level reduce college enrolment and increase school drop-out, respectively. In our paper, we exploit

[3]A large number of papers examine determinants of cross-country differences in intergenerational mobility, see Black and Devereux (2011) and Corak (2013) for a literature review

local variation, and link it further to labor market outcomes, focusing on the heterogeneity of the effects by parental background and its implications in terms of (occupational) intergenerational mobility.[4]

The rest of the paper is organized as follows. Section 2 develops a static Roy model where background-specific returns to education and educational choices combine to determine the intergenerational persistency of occupational status. In Section 3, we present the data used as well as some descriptive statistics on educational and occupational mobility. Section 4 presents our empirical specification. Main results are presented in Section 5 while channels and robustness checks are presented in Section 6. Finally, we conclude in Section 7.

2 Conceptual Framework

2.1 Setup

We develop a simple Roy Model of selection into education in an economy with two types of occupations (white and blue collar jobs). Suppose that individuals are distinguished by an unobserved ability type $z \sim N(\mu, \sigma^2)$, and that the returns to ability in the labor market depend on education and the occupation in which the individual will be employed – a blue or a white collar occupation. While education will affect wages within a given occupation as well as the probability of accessing a given occupation, unobserved ability z is restricted to solely affect the within-occupation component of wages. In other words there is random allocation to occupation within an educational group.

Assuming log-utility, the expected utility from labor income depending on education ($W_0(z)$ for low education, $W_1(z)$ for high education) can be written as:

$$W_0(z) = p_0^{wc} W_0^{wc}(z) + (1 - p_0^{wc}) W_0^{bc}(z)$$

$$W_1(z) = p_1^{wc} W_1^{wc}(z) + (1 - p_1^{wc}) W_1^{bc}(z)$$

[4]Incidentally, our findings contribute to the ongoing policy debate regarding the strong tendency of the French educational system to reproduce social inequality in terms of school performance (OECD, 2016) (See for instance NYT, "The Strangehold on French Schools" 09/11/2015). Our results show that the contribution of the educational system for social mobility depends not only on how socially biased it is against enrolled students but also on access. In the French case, the low cost of post-compulsory schooling contributes very likely to explain the relatively more counter-cyclical enrollment responses that we document by 16 year old with low parental-background thus sheltering them somewhat against business cycle fluctuations.

where p_i^h refers to the probability of obtaining occupation $h \in \{wc, bc\}$ (white collar, blue collar) conditional on having educational level $i = 0, 1$ (low, high). W_i^h refers to log-earnings from having job h conditional on education i. The wage earned for education level i, occupation h and unobserved ability z is given by a log-linear specification in z:

$$W_i^h(z) = \alpha_i^h + \beta_i^h z \text{ where } i = 0, 1 \text{ and } h = bc, wc$$

For both blue and white collar occupations, we assume that $\alpha_1^h > \alpha_0^h > 0$, meaning that education has an unconditional positive effect on earnings; and that $\beta_1^h > \beta_0^h > 0$, meaning that education and ability are complements, which will then imply that high-ability individuals are positively selected into education.

The expected log-income for education level i is given by :

$$W_i = \underbrace{(p_i^{wc}\alpha_i^{wc} + (1 - p_i^{wc})\alpha_i^{bc})}_{\equiv \alpha_i} + \underbrace{(p_i^{wc}\beta_i^{wc} + (1 - p_i^{wc})\beta_i^{bc})}_{\equiv \beta_i} \times z \qquad (1)$$

Given a cost of education c, individuals obtain education if:

$$W_1 - c \geq W_0 \Leftrightarrow z \geq \frac{\alpha_0 - \alpha_1 + c}{\beta_1 - \beta_0} \equiv z^*$$

Hence, all individuals of type $z \geq z^*$ obtain education, where:

$$z^* \equiv \frac{\alpha_0 - \alpha_1 + c}{\beta_1 - \beta_0} = \frac{c}{\beta_1 - \beta_0} - \eta$$

Where in turn, $\eta = \frac{\alpha_1 - \alpha_0}{\beta_1 - \beta_0}$ is the ratio of ability-unrelated over ability-related returns to schooling. Intuitively, if the returns to education are mostly independent of ability, the ability threshold will be lower; while if the complementarities between ability and education are high, the ability threshold will be higher. The ability threshold increases with the costs of schooling, weighted by the ability-related returns to education: if they are low, costs increase the ability threshold; if they are large, they have a smaller affect. Since z is normally distributed – $z \sim N(\mu, \sigma^2)$, we can write the probability of obtaining education $i = 1$ as:

$$P(z > z^*) = \Phi\left(\frac{\mu - z^*}{\sigma}\right) \equiv H(z^*)$$

In this model, the notion of wage upon which the educational decision is taken is lifetime earnings adjusted for job amenities – that is lifetime utility from accessing a given occupation, earnings being only one component of that utility. It is empirically difficult to deduce permanent income lifetime from a few observations at a single moment of the life-cycle (see e.g. Nybom and Stuhler, 2016).[5] Furthermore, at a conceptual level, it is not clear how to adjust income for job-specific amenities. These two difficulties contribute to motivate our focus on occupational choices and persistency. Occupational status presents the empirical advantage of being is rather stable past a certain age and observable with less measurement error – especially given the facts that we are relying on survey data for which wage information tend to be noisier than administrative data and we are using a rather coarse (and yet meaningful) occupation nomenclature. It presents the conceptual advantage of resulting from individual choices and random sorting within an educational group rather than being a variable that is part of the information set upon which decisions are taken.[6]

We investigate the probability of reaching a white collar occupation. More precisely we are interested in the probability of obtaining a white collar occupation conditional of the individual social background b which is either high (H) or low (L), meaning that her father occupies a blue collar and white collar job, respectively. We allow social background to affect the distribution from which ability is drawn, the returns to education function, and the probability of occupying a white-collar job conditional on education. The probability of being in a white collar occupation generated by the model is the following:

$$P(wc|b) = H(z_b^*)p_{b,1}^{wc} + (1 - H(z_b^*))p_{b,0}^{wc} \text{ where } b = H, L \tag{2}$$

, where $p_{b,1}^{wc}$ is the probability of obtaining a white collar occupation conditional on being educated and on parental background b. This simple model generates a transition matrix where $P(wc|b)$ depends on average educational attainment $H(z_b^*)$ – an endogenous object – and the background specific occupational-return to education, i.e. the difference between $p_{b,1}^{wc}$ and $p_{b,0}^{wc}$ – which are here considered as primitives of the model.

[5] Moreover we do not observe earnings for the entire sample period.

[6] In other words, the conceptually relevant earnings are a latent variable that drives the discrete (educational) choice. Current earnings being very noisy and likely biased proxy of the lifetime utility from an occupation, we do not study them and instead focus the empirical analysis on the resulting discrete choice.

2.2 The occupational mobility implications of the business cycle

A possible measure of social mobility is the probability of occupying a white collar conditional on having blue collar parents, $P(wc|L)$. However, empirically this measure is likely to be trending up because of the evolution of the economy, notably the increasing size of the tertiary sector. Because unemployment is trending up as well, at least for some subperiods, it can be difficult to identify the effect of unemployment on that measure. The same can be said of the overall measure of education attainment $P(z > z_L^*|L)$. Taking stock of these difficulties, we focus on the relative intergenerational mobility of individuals with low-background, that is the gap in the probability of obtaining a white collar job between children of high and low background:

$$\begin{aligned}\Delta &\equiv P(wc|H) - P(wc|L) \\ &= H(z_H^*)p_{H,1}^{wc} + (1 - H(z_H^*))p_{H,0}^{wc} - H(z_L^*)p_{L,1}^{wc} - (1 - H(z_L^*))p_{L,0}^{wc}\end{aligned}$$

The expression makes it clear that Δ depends on the transition probabilities by educational level ($\{p_{H,i}^{wc}, p_{H,i}^{wc}\}_{i=0,1}$) and educational attainment ($H(z_L^*), H(z_H^*)$).

Empirically, we model how Δ is affected by the business cycle using a linear probability model in the following way:

$$P(wc|b, u) = \gamma_0 \cdot u + \gamma_1 \cdot \mathbf{1}(b = H) + \gamma_2 \cdot u \times \mathbf{1}(b = H) \tag{3}$$

where $\mathbf{1}()$ is an indicator function and u is the (local) unemployment rate. The parameter γ_2 captures the following partial effect:

$$\gamma_2 = \left(\frac{\partial P(wc|B = H, u)}{\partial u} - \frac{\partial P(wc|B = L, u)}{\partial u}\right) = \frac{\partial \Delta}{\partial u}$$

According to our Roy model, we can reexpress γ_2 in the following way:

$$\begin{aligned}\gamma_2 &= \frac{\partial P(wc|H, u)}{\partial u} - \frac{\partial P(wc|L, u)}{\partial u} \\ &= H'(z_H^*)\frac{\partial z_H^*}{\partial u} \times (p_{H,1}^{wc} - p_{H,0}^{wc}) - H'(z_L^*)\frac{\partial z_L^*}{\partial u} \times (p_{L,1}^{wc} - p_{L,0}^{wc}) \qquad (4) \\ &+ \left(\frac{\partial p_{H,1}^{wc}}{\partial u}H(z_H^*) + \frac{\partial p_{H,0}^{wc}}{\partial u}(1 - H(z_H^*))\right) - \left(\frac{\partial p_{L,1}^{wc}}{\partial u}H(z_L^*) + \frac{\partial p_{L,0}^{wc}}{\partial u}(1 - H(z_L^*))\right) \qquad (5)\end{aligned}$$

Here, the first component (4) refers to the business cycle impact on occupational IGM that is driven by differential endogenous responses in educational attainment while the second component (5) refers to the business cycle impact that operates through changes in the transition matrix for each educational level. Regarding the first component, differential endogenous responses in educational attainment could arise for a number of reasons. First, because of differences in how the ability threshold $z^* \equiv \frac{\alpha_0-\alpha_1+c}{\beta_1-\beta_0}$ changes with the business cycle. One would expect z^* to be more elastic for children of low-skilled parents because of differences in returns to education by parental background, possibly because of complementarities with earlier investments (Cunha and Heckman (2008), Cunha *et al.* (2010)); or to differences in discount rates (Tanaka *et al.* (2010), Banerjee and Mullainathan (2010)). Another source of heterogeneous response could arise due to an increased children's attention towards employment prospects when making their schooling choices after changes in parental labor market success due to the business cycle, as shown by Huttunen and Riukula (2017). Besides the heterogeneity in changes in z^*, it is very likely that the number of students at the margin where economic conditions change the optimal level of schooling might differs by parental background. In particular, we would expect a larger share of children of low-skilled parents to be at the margin between obtaining post-compulsory schooling (or college) or not. Regarding the second component, changes in the transition matrix for each educational level - differences in the occupational returns to education by social background- could arise, for instance, due to different abilities of dealing with the scarring effects of unemployment.

Note that in our model, holding education constant is equivalent to holding $z^* = [z^*_H, z^*_L]$ fixed to specific value. Denoting this specific value by $\underline{z}$, γ_2 can be expressed as:

$$\begin{aligned}\gamma_2|_{z*=\underline{z}} &= \frac{\partial P(wc|H,u)}{\partial u}|_{z^*_H=z_H} - \frac{\partial P(wc|L,u)}{\partial u}|_{z^*_L=z_L} \\ &= \left(\frac{\partial p^{wc}_{H,1}}{\partial u}H(z^*_H) + \frac{\partial p^{wc}_{H,0}}{\partial u}(1-H(z^*_H))\right) - \left(\frac{\partial p^{wc}_{L,1}}{\partial u}H(z^*_L) + \frac{\partial p^{wc}_{L,0}}{\partial u}(1-H(z^*_L))\right)\end{aligned}$$

Therefore the difference between γ_2 and $\gamma_2|_{z*=\underline{z}}$ captures the component of the business cycle impact on occupational mobility that is due to endogenous educational responses to the business cycle. Empirically, we estimate equation (6) conditioning or not on a measure of educational attainment. The gap between the estimated coefficient captures the contribution of endogenous responses of education to the business cycle to the overall effect of the business cycle on occupational IGM. On the contrary, $\gamma_2|_{z*=\underline{z}}$ captures the IGM-implications of the business cycle that is related to changes in the transition matrix by education level.

Moreover, we empirically model the probability of obtaining a post-compulsory degree $P(i = 1|b)$ according to the same LPM as previously.

$$P(i = 1|b, u) = \delta_0 \cdot u + \delta_1 \cdot \mathbf{1}(b = H) + \delta_2 \cdot u \times \mathbf{1}(b = H) \tag{6}$$

Here, we have:

$$\begin{aligned} \delta_2 &= \frac{\partial P(i = 1|H)}{\partial u} - \frac{\partial P(i = 1|L)}{\partial u} \\ &= H'(z_H^*)\frac{\partial z_H^*}{\partial u} - H'(z_L^*)\frac{\partial z_L^*}{\partial u} \end{aligned}$$

This expression is related to $\gamma_2 - \gamma_2|_{z^*=\underline{z}}$. In fact, we have that $\gamma_2 - \gamma_2|_{z^*=\underline{z}} \propto \delta_2$ if $p^{wc}_{H,1} - p^{wc}_{H,0} = p^{wc}_{L,1} - p^{wc}_{L,0}$. That is the component of the effect of the business cycle on occupational mobility that is driven by the differential educational response to the business cycle between individuals with high and low social background is proportional to that differential educational response as long as the occupational returns to education are equal across parental background. Moreover, we would have $\gamma_2 - \gamma_2|_{z^*=\underline{z}} = \delta_2$ if $p^{wc}_{H,1} - p^{wc}_{H,0} = p^{wc}_{L,1} - p^{wc}_{L,0} = 1$, that is educational and occupational mobility would be affected identically by the business cycle in a world where getting a post-compulsory degree is a sufficient and necessary condition for accessing a white collar job – which obviously does not hold empirically.

To sum up, in the model occupational IGM is a function of educational attainment across parental background and of parental background-specific occupational returns to education. Accordingly, business cycles can affect the occupational IGM either through the endogenous educational responses it triggers or through changes in occupational returns to education. By estimating the model holding or not education fixed, we can assess the share of the occupational IGM implications of the business cycle that is due to either mechanism. We now present to the data we will use in the empirical applications.

3 Data and Descriptive Statistics

We use the French Labor Force Survey, from 1990 to 2014, merged with national and départemental unemployment data from 1982 to 2014.[7] We keep all individuals older than 25 at the time of the

[7]From 1990 to 2002, the LFS is yearly, from 2003 onwards, it is quarterly. The version of the LFS used are referenced as follows: Enquête Emploi en continu (version FPR) - 1982/2014, INSEE [producteur], ADISP-CMH [diffuseur].

survey; and for which we have information on the unemployment rate at the time of choosing schooling (i.e., those born between 1965 and 1988). We obtain a sample of slightly more than 190000 individuals, corresponding to 22 cohorts across 96 départements, with an average and a median N of 300 and 223 individuals by cohort-département. The average age of individuals at the time of the survey is 33, with a maximum age of 48. For every individual, we observe educational attainment and both own and parental labor market occupation (by skill category).

We classify individuals (and parents) as being blue or white collars. In particular, blue collars are employee and (factory) worker (respectively employés and ouvriers in French), and white collars are executive or other high position as well as Intermediate occupations (respectively cadres and professions intermédiaires in French). We exclude individuals whose parents are in heavily self-employed occupations such as Farmer, Craftsman or Shopkeeper.

The education variable describes the highest degree obtained by the individual, which can be one of the following: No diploma, end of middle school degree (9th grade), early vocational training degree (CAP), Technical degree, technical or vocational senior high school degree (Tech. and Pro. Baccalauréat), general senior high school degree (Baccalaurat), Undergraduate diploma (two years after the Baccalauréat), Bachelor's degree (three years after the Baccalauréat), Graduate diploma (four years after the Baccalaurat), and higher degree (Master's and PhD). We consider as individuals with no post-compulsory degree those who hold no diploma, an end of middle high-school or a CAP. All the others are considered as holding a post-compulsory degree. People holding a degree strictly above high-school are classified as being college-educated and having completed some higher education.

Data on the local unemployment rate are provided by INSEE. The unemployment rate is computed using administrative data on both job seekers and local employment. While the exhaustive nature of the data ensures the quality of the unemployment rate at the local level over the period, the data does not allow us to obtain unemployment by age, skill or gender.[8]

Table 1 and table 2 report descriptive statistics. In table 1, the sample is split according to the workers' skill category once in the labor market. Throughout the paper, we use white collar and high-skilled jobs interchangeably. The descriptive statistics show that white collars are more likely to hold post-compulsory degrees; and much more likely to hold college degrees. More than half of the white collar workers had a white collar father, and compared to children of blue collars, they

[8]It is calculated by combining administrative data from the public employment agency on job seekers (to build the denominator), and several other administrative sources to build reliable statistics on local employment. The resulting data are then calibrated in order to match the survey data on the unemployment rate according to the ILO definition.

are more than twice as likely to have a white-collar father. On the other hand, in table 2 the sample is split according to the workers' parental skill category. The descriptives show that children of white collars are more likely to hold post-compulsory degrees; and much more likely to hold college degrees. Moreover, two thirds of white collar children end up in white collar occupations, and compared to children of blue collars, they are twice as likely to be employed as a white collar workers. The differences in educational attainment by parental skill (table 2) are smaller than the differences by own skill (table 1), suggesting that there is some mobility. However, the differences remain large, indicating a substantial amount of interegenerational persistence in economic status. In addition, the descriptives suggest that our binary measure of economic status is a meaningful measure.

Finally, figures 1 and 2 display the parental background gap in terms of post compulsory school completion and and access to white collar jobs – respectively denoted $H(z_H^*) - H(z_L^*)$ and Δ in our conceptual framework – for the different cohorts of our sample. The figures display large differences in labor market success by parental background, and a positive correlation between the parental background gap in post-compulsory educational attainment and the parental background gap in the probability of obtaining a white collar job.[9]

Table 1: Occupation measure and covariates

	All	Blue Collar	White Collar
Post Compulsory Education	0.837	0.742	0.957
	(0.370)	(0.438)	(0.204)
University Degree	0.400	0.145	0.723
	(0.490)	(0.352)	(0.448)
White Collar Father	0.361	0.218	0.543
	(0.480)	(0.413)	(0.498)
National Unemp. rate at age 16	8.809	8.769	8.861
	(1.043)	(1.037)	(1.049)
Local Unemp. rate at age 16	8.517	8.561	8.461
	(2.138)	(2.130)	(2.148)
Year of birth	1973.4	1973.1	1973.7
	(5.636)	(5.652)	(5.601)
Observations	198063	110672	87391

Standard deviation in parenthesis

[9]The two series (raw and smoothed) are plotted against time in Figure A1 of the Appendix.

Table 2: Parental Occupation measure and covariates

	All	Blue Collar Father	White Collar Father
Post Compulsory Education	0.837	0.785	0.927
	(0.370)	(0.411)	(0.260)
University Degree	0.400	0.267	0.634
	(0.490)	(0.443)	(0.482)
White Collar	0.441	0.316	0.663
	(0.497)	(0.465)	(0.473)
National Unemp. rate at age 16	8.809	8.780	8.862
	(1.043)	(1.040)	(1.047)
Local Unemp. rate at age 16	8.517	8.553	8.453
	(2.138)	(2.127)	(2.157)
Year of birth	1973.4	1973.1	1973.7
	(5.636)	(5.593)	(5.691)
Observations	198063	126505	71558

Standard deviation in parenthesis

Figure 1: Achievement by Cohort × PB

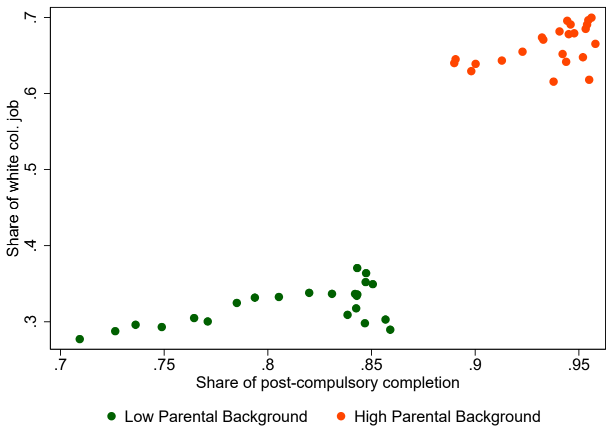
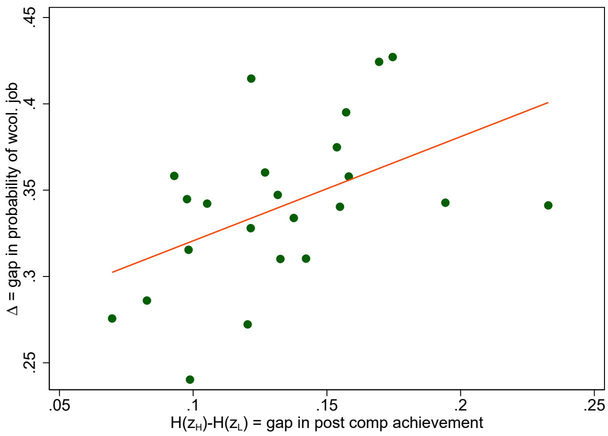


Figure 2: Achievement Gap by Cohort



Note:

4 Empirical Specification

Our baseline specification is the following:

$$\begin{aligned}\text{Outcome}_i =&\beta_0 + \beta_1 \text{High PB}_i + \beta_2 U^{bpl}_{16,i} \\ &+ \boldsymbol{\beta_3} (U^{bpl}_{16} \times \text{High PB})_i + X_i' \beta_4 + \epsilon_i\end{aligned} \tag{7}$$

where U^{bpl}_{16} refers to the unemployment rate prevailing in the place of birth of individual i when she was 16 (i.e., bpl stands for birthplace). We regress the outcome of interest of individual i on a dummy for having a white collar father, the unemployment rate at age 16, and the interaction between the two. Our coefficient of interest is β_3. Since children of white collar father have better outcomes on average, a negative β_3 would imply that the parental background gap is smaller for cohorts exposed to bad economic conditions at age 16.

We estimate this regression on two outcomes. To measure Educational Intergenerational Mobility, we will use a dummy for holding a post-compulsory degree; and a dummy for holding a college degree (in the college degree specifications, our measure of economic conditions will be unemployment at age 18). To measure Occupational Intergenerational Mobility, we will use a dummy for being employed in a white collar occupation. First, we present results exploiting variation in national economic conditions, then we exploit variation in local (département level) conditions as well. Since we observe the individuals' département of birth, we will use the unemployment rate corresponding to that département, to avoid biases due to family sorting across départements due to labor market conditions. We focus on the unemployment rate at age 16 because it is the first period in which individuals have to make a choice, given that all individuals are enrolled in school until age 16. Moreover, this minimizes the simultaneity bias between unemployment rates and school enrolment rates.

Our most demanding specification will include département by year of birth fixed effects, that absorb all unobserved heterogeneity within a cohort in a province, département by parental occupation fixed effects, that absorb all time-invariant differences in unobserved differences between white and blue collars that might systematically change across départements, and département by parental background time trends. Occupational Mobility regressions feature additional controls -survey year by birth year fixed effects and age at survey by parental skill fixed effects-, to allow for heterogeneous career profiles by age and parental background (Lee and Solon, 2009). All regressions are estimated by OLS, and include a gender dummy as a control. Standard errors are clustered at the département by parental skill level, except for regressions exploiting variation in the national unemployment rate, when we report White-Huber heteroskedasticity-robust standard errors.

5 Main Results

5.1 Educational mobility

We start with very simple correlations, and move step by step towards more flexible specifications. The first column in table 3 reports the estimates of a regression of holding a post-compulsory degree on national unemployment at age 16, a dummy for having a white collar father, and its interaction, without any other controls. The results show that there is positive relationship between bad economic conditions at age 16 and the probability of holding a post-compulsory degree, and that children of high skilled parents are significantly more likely to obtain post-compulsory education. Our parameter of interest shows that the children of the low skilled are the most counter-cyclical. This means that cohorts deciding on education in recessions are more intergenerationally mobile. Including year of birth fixed effects and département by parental skill fixed effects does not significantly change the results. For every regression, we report $\widehat{\beta} \times \frac{\Delta U_{25}^{75}}{\text{gap}}$, which measures by how much a variation in the unemployment rate from the 75th to the 25th of the distribution changes the educational gap between children of blue and white collar workers, with respect to the unconditional sample average gap. According to these first estimates, being exposed to a high national unemployment rate at the moment of choosing post-compulsory education reduces the average parental background gap in post-compulsory attainment by slightly more than 10%.

Table 4 reports estimates of the same relationship, but exploiting variation in economic conditions at the département level. These regressions include département by parental skill fixed effects and either cohort fixed effects or cohort by département of birth fixed effects. The estimates in table 4 indicate that being exposed to a high regional unemployment rate (75th vs. 25th percentile) at the moment of choosing post-compulsory education reduces the parental background gap in post-compulsory attainment by more than 20%.

Table 5 reports estimates with the same specification and variation as in table 4, but with a dummy for holding a college degree as an outcome, and using unemployment at age 18 rather than at age 16 as an explanatory variable. The estimates in table 5 show that college attainment is pro-cyclical rather than counter-cyclical with respect to local economic conditions. Again, the

Table 3: Post-compulsory schooling and national unemployment rate at 16

	(1) PostComp	(2) PostComp	(3) PostComp
National UR at age 16	3.077***		
	(0.109)		
National UR at age 16 × *HighPB*	-1.700***	-1.635***	-1.638***
	(0.142)	(0.161)	(0.165)
High Parental Background	28.92***	27.89***	
	(1.285)	(1.549)	
Adjusted R^2	0.043	0.054	0.054
Cohort FE		✓	✓
Dept FE		✓	
Dept × PB FE			✓
Mean Gap in Outcome	14.2 pp	14.2 pp	14.2 pp
$\widehat{\beta} \times \frac{\Delta U_{25}^{75}}{\text{gap}}$	-11.9%	-11.4%	-11.4%
Observations	198063	198063	198063

Notes: Robust standard errors in parentheses. All regressions control for gender. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Post-compulsory schooling and departmental unemployment rate at 16

	(1) PostComp	(2) PostComp
Birth place UR at age 16	0.568***	
	(0.163)	
BP UR at age 16 × *HighPB*	-1.300***	-1.214***
	(0.141)	(0.0962)
Adjusted R^2	0.054	0.054
Cohort FE	✓	
Dept × PB FE	✓	✓
Dept × Cohort FE		✓
Mean Gap in Outcome	14.2 pp	14.2 pp
$\widehat{\beta} \times \frac{SD}{\text{gap}}$	-25.6%	-23.9%
Observations	198063	198046

Notes: Robust standard errors in parentheses – clustered at the département × white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

children of the low skilled are relatively less pro-cyclical, meaning that the results have the same implication regarding business cycle fluctuations and educational mobility. The point estimates in table 5 suggest that being exposed to a high départemental unemployment rate at the typical moment of choosing college education reduces the parental background gap in college degree attainment by around 4%. Table A1 in the Appendix reports results both for post-compulsory schooling and college, allowing by differential trends at the département by parental background level. The coefficient of interest for post-compulsory education becomes smaller in magnitude, but in both cases the qualitative implications remain similar, economically and statistically significant.

Table 5: College degree and departmental unemployment rate at 18

	(1) College	(2) College
$U^{bpl}_{18,d}$	-0.376*	
	(0.200)	
$U^{bpl}_{18,d} \times$ High PB	-0.552**	-0.513***
	(0.219)	(0.150)
Adjusted R^2	0.159	0.159
Cohort FE	✓	
Dept × PB FE	✓	✓
Dept × Cohort FE		✓
Mean Gap in Outcome	36.7 pp	36.7 pp
$\widehat{\beta} \times \frac{\Delta U^{75}_{25}}{\text{gap}}$	-4.5%	-4.2%
Observations	195204	195200

Notes: Robust standard errors in parentheses – clustered at the département × white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Occupational intergenerational mobility

The previous results show that cohorts exposed to bad economic conditions at the moment of making important schooling choices are more intergenerationally mobile in terms of educational attainment. We now ask whether these cohorts perform differently in the labour market as well. To this aim, we study how exposure to the business cycle relates to intergenerational occupational mobility, defined as the probability of having a white collar job conditional on having a white collar father. According to our conceptual framework of positive selection into education by ability, with complementarities between ability and schooling, the business cycle compliers are likely to have relatively low returns to schooling, which could explain a null effect on occupational mobility in spite of a positive effect on educational mobility. On the other hand, we have seen in table 3 that on average, those cohorts obtain more schooling, and in general equilibrium this could lower the return to schooling for the whole cohort, which would reinforce the effect on educational mobility and lead to increased occupational mobility.[10].

To answer this question, we estimate the same regressions, using a dummy for being employed as a white collar as an outcome. The empirical specification is very similar. Given that we measure the labor market outcome of individuals at different ages and in different years, we add survey year by birth year fixed effects. To further allow for heterogeneous career profiles by age and parental background (Lee and Solon, 2009), we include age at survey by parental skill fixed effects.

We start with correlations at the national level. Table 6 reports estimates of the relationship between the national rate of unemployment at age 16 and the probability of being employed in a white collar occupation, by parental occupation. The patterns in this table are very similar to those in table 3: individuals in cohorts exposed to worse economic conditions at age 16 are significantly more likely to become white collar workers, and this pattern is stronger for the children of the low skilled, that have a lower unconditional probability of becoming white collar workers. The point estimates in table 6 suggest that being exposed to a high national unemployment rate at the moment of choosing post-compulsory education reduces the intergenerational elasticity of white collar employment by around 1.7%.

Table 6: Occupational status and national unemployment rate at 16

	(1) White Collar	(2) White Collar	(3) White Collar	(4) White Collar
U_{16}^{nat}	1.680*** (0.126)			
U_{16}^{nat} × High PB	-0.481** (0.210)	-0.621*** (0.224)	-0.606** (0.240)	-0.595** (0.245)
High PB	38.82*** (1.867)			
Adjusted R^2	0.114	0.123	0.130	0.130
Age × PB FE		✓	✓	✓
Cohort × Survey FE		✓	✓	✓
Dept FE			✓	
Dept × PB FE				✓
Mean Gap in Outcome	34.7 pp	34.7 pp	34.7 pp	34.7 pp
$\widehat{\beta} \times \frac{\Delta U_{25}^{75}}{\text{gap}}$	-1.4%	-1.8%	-1.7%	-1.7%
Observations	198109	198109	198109	198109

Notes: Robust standard errors in parentheses. All regressions control for gender. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[10]This would happen as long as the scarring effects of unemployment for those choosing not to go to school are large enough so that the returns to schooling within the cohort end up increasing

Table 7 reports estimates of the same relationship, but exploiting variation in départemental economic conditions. The results are stable across specifications and have similar implications. The point estimates in table 7 suggest that being exposed to a high départemental unemployment rate at the moment of choosing post-compulsory education reduces the intergenerational elasticity in white collar employment by around 4.4%. Table A2 in the Appendix reports very similar results for départemental unemployment at age 18. Table A3 in the Appendix reports results that control for department by parental background trends, with similar point estimates as well.

Table 7: Occupational status and departmental unemployment rate at 16

	(1) White Collar	(2) White Collar	(3) White Collar
$U^{bpl}_{16,d}$	-0.0564		
	(0.220)		
$U^{bpl}_{16,d} \times$ High PB	-0.480**	-0.577***	-0.540***
	(0.198)	(0.174)	(0.146)
Adjusted R^2	0.123	0.130	0.130
Dept $\times$ PB FE	✓	✓	✓
Cohort FE	✓	✓	
Cohort $\times$ Dept FE			✓
Age $\times$ PB FE		✓	✓
Cohort $\times$ Survey FE		✓	✓
Mean Gap in Outcome	34.7 pp	34.7 pp	34.7 pp
$\widehat{\beta} \times \frac{\Delta U^{75}_{25}}{\text{gap}}$	-3.9%	-4.7%	-4.4%
Observations	198109	198109	198092

Notes: Robust standard errors in parentheses – clustered at the département $\times$ white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Hence, overall, the results suggest that the fluctuations in schooling related to the business cycle have long-run consequences, with significant effects on the degree of intergenerational mobility in white collar occupations, with exposure to different conditions leading to a change in the intergenerational white-collar elasticity of around 4.5%. On the other hand, Pekkarinen *et al.* (2009) report a 23% reduction in the intergenerational elasticity of income in Finland after a major educational reform that shifted the selection of students to vocational and academic tracks from age 11 to age 16. Hence, although significant, the role of the business cycle for intergenerational mobility remains considerably small compared to structural changes in the educational system. It is however likely that the structural parameters of the educational system (e.g. selectivity, out-of-pocket cost for students, ease of access to credit) determine how the business cycle affects schooling choices differentially across parental background and in turn occupational intergenerational mobility. Investigating this question using our empirical approach would require an exploitable change in those parameters within a cohort, which we lack over the sample period. We therefore leave it to further research.

6 Channels and Robustness

6.1 Educational attainment and occupational mobility

Our conceptual framework and our previous results highlight the role of endogenous responses in educational attainment for the effect of the business cycle on intergenerational mobility. We next estimate how much of the effect on occupational mobility is driven by such changes, keeping in mind that education is an endogenous or bad control, since it is a channel, and the coefficient of interest will be biased towards zero or towards finding the opposite result. Tables 8 and 9 report intergenerational occupational mobility regressions, controlling for educational attainment, which makes the unemployment rate coefficients becomes substantially smaller and less precisely estimated as well. The results show that changes in educational attainment explain most of the effect of the cycle on mobility (between 60% and 70%).

Table 8: Occupational status and departmental unemployment rate at 16

	(1) PostComp	(2) White Collar	(3) White Collar
$U^{bpl}_{16,d} \times$ High PB	-1.280***	-0.540***	-0.144
	(0.110)	(0.146)	(0.150)
PostComp			31.05***
			(0.666)
Adjusted R^2	0.055	0.130	0.180
Dept × PB FE	✓	✓	✓
Cohort × Dept FE	✓	✓	✓
Age × PB FE	✓	✓	✓
Cohort × Survey FE	✓	✓	✓
Mean Gap in Outcome	14.2 pp	34.7 pp	34.7 pp
$\widehat{\beta} \times \frac{\Delta U^{75}_{25}}{\text{gap}}$	-25.2%	-4.4%	-1.2%
Observations	198046	198092	198046

Notes: Robust standard errors in parentheses – clustered at the département × white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Occupational status and departmental unemployment rate at 18

	(1) College	(2) White Collar	(3) White Collar
$U^{bpl}_{18,d} \times$ High PB	-0.572***	-0.521***	-0.211
	(0.150)	(0.186)	(0.168)
College			54.9***
			(0.519)
Adjusted R^2	0.160	0.130	0.376
Dept $\times$ PB FE	✓	✓	✓
Cohort $\times$ Dept FE	✓	✓	✓
Age $\times$ PB FE	✓	✓	✓
Cohort $\times$ Survey FE	✓	✓	✓
Mean Gap in Outcome	36.7 pp	34.7 pp	34.7 pp
$\widehat{\beta} \times \frac{\text{U pctile}^{75}_{25}}{\text{gap}}$	-4.7%	-4.2%	-1.7%
Observations	195200	195238	195200

Notes: Robust standard errors in parentheses – clustered at the département $\times$ white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Accounting for spatial mobility between birth and age 16

Exploiting cross-sectional variation in local unemployment rates allows us to control flexibly for aggregate trends in school attainment by including cohort fixed-effects. Using birthplace unemployment rates allows us to rule out geographical sorting based on economic conditions. However, we need to assess the strength of the association between birthplace and location at 16 unemployment rate and whether it varies by parental background to make sure that our results are not driven by differential geographical mobility by parental background. To this aim, in this subsection we start by describing the pattern of mobility between birth and age 16 and how it affects the relationship between birthplace unemployment rate at age 16 and place of residence unemployment rate at age 16. After that, we study how this relationship varies by parental background and account for it by using a Two-Sample 2SLS estimator.

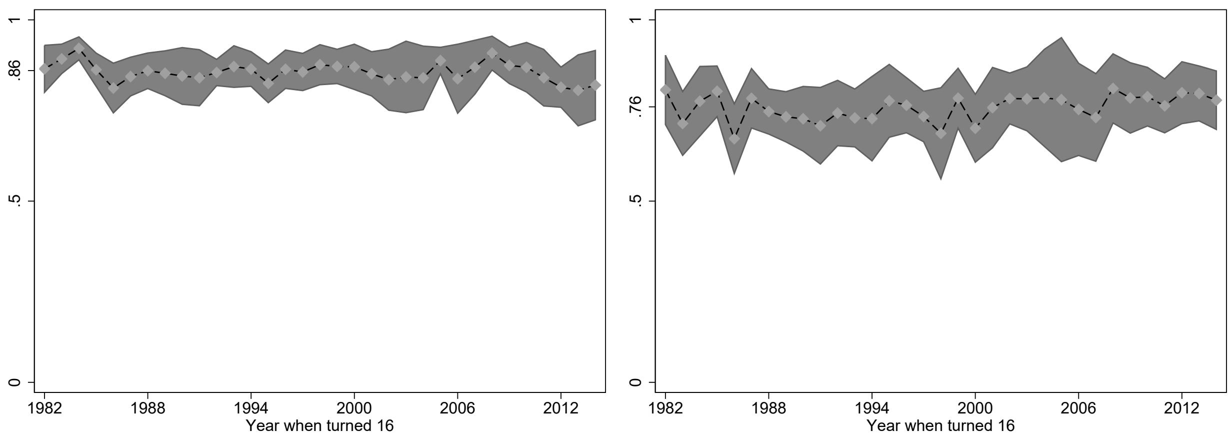
6.2.1 Descriptive evidence

Our sample comprises individuals aged 25 or more at the time of the survey interview, for whom we know the département of birth but not the département of residence (and hence their actual exposure to the business cycle) at age 16. We can however examine the relationship between the prevailing unemployment rates in the département of birth and the département of residence at age 16, by selecting individuals age 16 at the time of the survey in the waves of the French LFS from

1982 to 2014. For those individuals, we can check how strong this relationship is and to which extent it varies with parental background.

To this aim, Figures 3 display cohort and parental background specific OLS coefficients from the regression of local unemployment in the current place of residence at age 16 (denoted U_{16}^{cur}) onto the local unemployment rate in the place of birth (U_{16}^{bpl}). The coefficients are remarkably stable over time. Moreover they are rather similar across family background suggesting that the differential impact of birthplace unemployment rate at age 16 on educational and occupational attainment is unlikely to reflect differential geographical mobility across parental background. Nevertheless, the relationship between U_{16}^{cur} and U_{16}^{bpl} is significantly stronger for children of low parental background. To investigate this more formally we now proceed to an instrumental variables estimation whereby we instrument place of residence rate by birthplace unemployment at age 16.[11]

Figure 3: Relationship between Birth Place and Residence at 16 Unemployment Rate for Different Cohorts



Low parental background High parental background

Note: Each dot corresponds to a distinct OLS regression of U_{16}^{cur} on U_{16}^{bpl} for each cohort and parental background. Shaded area correspond to 95% confidence intervals constructed using "parental background × départment of birth" clustered standard errors. The difference between the (pooled) coefficient of low and high parental background individual is equal to -0.077 and is statistically significant (t-value = 7.07). Cohort-specific differences are significant at the 5% level for 16 of the 22 cohorts.

[11] In subsection 6.3, we investigate this issue by focusing on school enrollment – a different outcome than in the main analysis for which we can implement an instrumental variable approach that explicitly accounts for the slight differential in mobility across family background that is visible in Figure 3.

6.2.2 Correcting for differential mobility by parental background

In this subsection, we take stock of the slight difference in the relationship between birthplace and place of residence at age 16 by parental background induced by differential patterns of geographical mobility. In order to correct for it, we set-up a Two-Sample 2SLS estimation whereby place of residence unemployment rate at age 16 is instrumented by place of birth unemployment rate at age 16.

The main complication to set up an IV estimation stems from the fact that we never observe the final outcome (educational attainment or occupational status) in the same sample as both the instrument (place of birth unemployment rate) and the endogenous variable (place of residence unemployment rate). Indeed, in the main sample (which we for simplicity we will refer to as sample 1) we focus on individuals who are unlikely to increase further their educational attainment – in our analysis people of age 25 or more –, but we ignore where they were living at age 16 – we only know their place of birth, from which we infer place of birth unemployment rate at age 16. On the other hand in the sample used in the subsection above (referred to as sample 2), we observe individuals of age 16 in different waves of the survey, about whom we know their place of residence at age 16 as well as their place of birth, but ignore their final educational attainment. This setting allows us to implement an estimation based on Two Sample 2SLS whereby the first stage is estimated using sample 2, the endogenous regressor is then predicted among observations in sample 1, and the second stage is then estimated running OLS using the generated regressor. Figure A2 in the Appendix illustrates the estimation procedure. Results are displayed in table 10 for specifications similar to the one in table 8 – in terms of covariates and fixed-effect. Results are remarkably similar, suggesting that the non-negligible differences in geographical mobility in response to local unemployment across parental backgrounds did not affect our reduced-form results substantially.

6.3 Training status at age 17

The main analysis relies on highest educational attainment (HEA) as a measure of investment in human capital. Using this measure presents two advantages. First, it allows to have a larger sample size, because HEA is documented for individuals of all ages. Second and most importantly, it allows us to look at longer run outcomes by examining the occupational status of individuals who

Table 10: Two-Sample 2SLS estimates of the effect of departmental unemployment rate at 16 on post Compulsory and Occupational

	(1) PostComp	(2) White Collar	(3) White Collar
$U^{cur}_{16,d}\times$ High PB	-1.479***	-0.624***	-0.166
	(0.132)	(0.178)	(0.182)
Post Comp			31.02***
			(0.643)
Dept $\times$ PB FE	✓	✓	✓
Dept $\times$ Cohort FE	✓	✓	✓
Age $\times$ PB FE	✓	✓	✓
Cohort $\times$ Survey	✓	✓	✓
Observations	198046	198092	198046

Notes: Bootstrapped standard errors (500 replications) in parentheses – clustered at the département $\times$ white collar father level. All regressions control for gender. Each replication of the bootstrap entails the estimation of both the first and second stages of the TS-2SLS procedure. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

are well into their working lives – we focus on individuals aged 25 or more.[12] Nonetheless, an alternative and complementary approach to analyse the impact of the business cycle on schooling is to investigate the impact of local unemployment at age 16 on the likelihood of being in training or not at age 17. This is feasible because of the short longitudinal nature of the data. Individuals are, absent a special event, surveyed 3 times in the annual surveys (hence over 3 years over the survey period 1982 to 2002) and 6 times in the quarterly survey (hence over a year and a half over the survey period 2003-2014).

In this subsection, we show that individuals experiencing a high place of birth unemployment rate at age 16 are more likely to be in training in the following year. The definition of training we consider includes internship as well vocational training.[13] We estimate the following equation:

$$T_{17,i} = \alpha + \beta_1 \cdot (U^{bpl}_{16} \times \text{High PB})_i + X_i'\delta + \mathbf{FE}_i + \varepsilon_i \tag{8}$$

where $T_{17,i}$ is binary variable equal to one if individual i is following a training at age 17. Exogenous controls in X include a binary variable for gender and parental background. $\mathbf{FE}_i$ refers to a set of fixed-effects that include département $\times$ parental background as well as département $\times$

[12] Moreover, the highest degree obtained is a rather unambiguous concept and a salient event in one's lifetime, therefore it seems unlikely to be subjected to recall bias.

[13] That definition corresponds to the category "student or intern following a training" in the nomenclature of activity status elaborated by the International Labor Organization.

year (so that only the interaction term between parental background and local unemployment is identified).

Equation 8 is a reduced-form in the sense that what matters causally for educational choices is the unemployment rate in the current location of residence at age 16 and not the one in the place of birth. However, current location unemployment at age 16 (U_{16}^{cur}) is likely to be endogenous with respect to training status at age 17. For instance, one could argue that more altruistic parents are more prone to move from high to low unemployment areas and are also more likely to encourage their children to follow longer training. To circumvent this issue we can use U_{16}^{bpl} as instrument for U_{16}^{cur}. We know from the subsection above that U_{16}^{bpl} is a statistically strong predictor of U_{16}^{cur}. Under the assumption that U_{16}^{bpl} is exogenous with respect to $T_{17,i}$ in equation 8, it constitutes a valid instrument for U_{16}^{cur}.[14]

The results in table 11 are in line with our previous findings, with the IV estimates (column 2) suggesting even a larger relative counter-cyclicality of the children of the low skilled – in line with the Two-Sample 2SLS evidence displayed in Table 10. A one-percentage point decrease in the local unemployment rate at age 16 decreases the likelihood of being in training relatively more for low-skill individuals by 1 percentage point.

Table 11: Training and departmental unemployment rate, dépt of birth, at 16

	(1) Reduced Form	(2) Reduced Form	(3) Reduced Form	(4) Reduced Form
Unemployment Rate	1.346***	2.071***	0.0320	
	(0.350)	(0.475)	(0.787)	
$U_{16,d}^{cur}\times$ High PB		-1.982***	-2.094***	-1.547***
		(0.561)	(0.530)	(0.417)
Dept $\times$ PB FE	✓	✓	✓	✓
Cohort FE			✓	
Dept $\times$ Cohort FE				✓
K-P stat	5163	651	318	1974
Observations	13337	13337	13337	13173

Notes: Robust standard errors in parentheses – clustered at the département $\times$ white collar father level. All regressions control for gender.* p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01.

[14] We can therefore estimate the following system of equation using 2SLS:

$$(U_{16}^{cur} \times \text{High PB})_i = \alpha^{FS} + \beta_1^{FS} \cdot (U_{16}^{bpl} \times \text{High PB})_i + X_i'\delta^{FS} + \mathbf{FE}_i + \varepsilon_i \quad \text{(1S)}$$
$$T_{17,i} = \alpha + \beta_1 \cdot (U_{16}^{cur} \widehat{\times \text{High PB}})_i + X_i'\delta + \mathbf{FE}_i + \varepsilon_i \quad \text{(2S)}$$

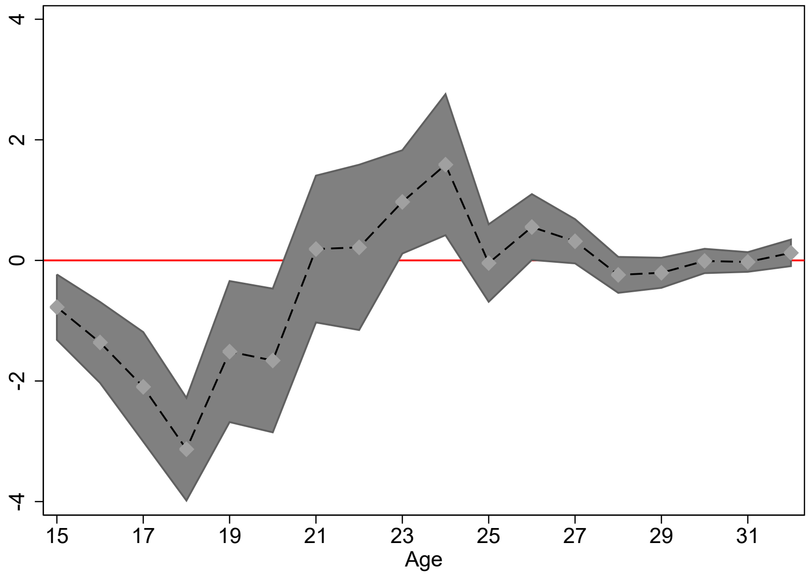
6.4 The reactivity of the training status for different ages

As a way to validate the method used, we estimate specification 8 but shifting the age at which unemployment and subsequent training are observed by one year, starting at age 15. If the results presented above were merely reflecting a mechanical relationship between our definition of training at time $t + 1$ and local unemployment rate at time t and we do not expect this mechanical relationship to vary by age, we should find relatively stable coefficients across ages. On the contrary, if the coefficient captured a causal relationship between unemployment and individuals' decision to enroll or remained in training, we would expect individuals in their late teens and early 20s to be very reactive, while we would not expect individuals in their late 20s or 30s to be as reactive. We would therefore expect to find negative coefficients for young individuals, and see these coefficients become closer to zero as we consider older individuals.

The latter prediction is broadly supported by results displayed in Figure 4. The figure shows the coefficients of separate IV regressions, which estimate the differential response of low versus high parental background individuals for individuals from age 15 to 33. We see that the gap in response is negative from ages 15 to 20 and becomes closer to zero and even switches sign for individuals aged 23 and 24. It then declines and becomes indistinguishable from zero for age 25 and beyond. As suggested by our previous results, children of high parental background are relatively less responsive to the local business cycle in their late teens, but that difference is reversed at age 22. This is consistent with individuals with high parental background using higher education as a buffer in responses to local labor market conditions, and low parental background individuals adjusting relatively more through post-compulsory education.[15] Overall, these results suggest a causal effect of local unemployment on individual training decision and show that late teenage years are particularly relevant for individuals whose father is a blue-collar.

[15] Note that the large difference in estimated coefficients between blue collar and white collar children around age 22 that we observe in Figure 4 could reflect (i) a stronger response of high parental background individuals conditional on being enrolled in training at t and (ii) the fact that individuals are more responsive to poor local economic conditions when they are already enrolled at time t and that a larger share of high parental background students are enrolled in training around age 22. We isolate the channel mentioned in (i) by restricting the sample to individuals already in training at time t. The estimation is carried out for individuals age 15 to 24 at time t. However, conditioning on previous training we run out of observations to fit our specification with département $\times$ PB and cohort fixed effects when considering individuals 24 or more. Results are displayed in figure A3 in the Appendix. The patterns are qualitatively close to those displayed in Figure 4, with negative coefficients for individuals in their late teenage years and positive coefficient for individuals in their early twenties. Coefficients are however imprecisely estimated for individuals more than 20 due to the lower number of observations.

Figure 4: The differential effect of local unemployment rate on training for different ages



Note: Each dot corresponds to a distinct IV regression of a binary variable for training at $t+1$ on the interaction between unemployment and parental background, for individuals of given age which is displayed in the x-axis. The second stage of the 2SLS estimation is given by equation (2S) – in footnote 14. Controls include gender and cohort as well as département $\times$ parental background fixed-effects. Local unemployment rate is instrumented by birth place unemployment rate. Shaded area correspond to 95% confidence intervals constructed using "cohort $\times$ département of birth" clustered standard errors.

7 Conclusion

This paper studies how economic conditions at the time of choosing post-compulsory education affect intergenerational mobility. Using a large dataset and exploiting variation in the unemployment rate in individuals' département of birth at age 16 across 96 French départements and 22 cohorts, we find that cohorts deciding on post-compulsory education in bad economic times are more educationally mobile - their level of education is less related to having a white collar father. We find that this translates into differences in labor market performance, since these cohorts are also more occupationally mobile – their probability of having a white collar job once in the labor market is less related to having a white collar father; and that a large fraction of the effect on occupational mobility is explained by differences in educational attainment. Quantitatively, our findings imply that within cohorts deciding on education in a high moment of the cycle (25th percentile of unemployment rate), the probability of having a white collar job conditional on having a white collar father increases by 5%, compared to cohorts deciding in a low moment of the cycle (75th percentile). Hence, our findings suggest that especially for children of the low skilled, changes in the opportunity cost of schooling have more traction in driving schooling decisions than changes in the ability to pay induced by the business cycle.

Our results unveil a channel through which the transmission of economic advantage arises and fluctuates across cohorts, contributing to the literature on the determinants of inter-generational mobility within countries - an exercise that is very data demanding. The findings complement to existing evidence outlining that economic shocks at crucial stages in life can have significant long-run effects.

References

AARONSON, D. and MAZUMDER, B. (2008). Intergenerational Economic Mobility in the United States, 1940 to 2000. *Journal of Human Resources*, **43** (1).

ALTONJI, J. G., KAHN, L. B. and SPEER, J. D. (2016). Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success. *Journal of Labor Economics*, **34** (S1), S361 – S401.

ANGRIST, J. D. and KRUEGER, A. B. (1992). The effect of age at school entry on educational attainment: An application of instrumental variables with moments from two samples. *Journal of the American Statistical Association*, **87** (418), 328–336.

APARICIO-FENOLL, A. (2016). Returns to education and educational outcomes: The case of the spanish housing boom. *Journal of Human Capital*, **10** (2), 235–265.

ARULAMPALAM, W. (2001). Is Unemployment Really Scarring? Effects of Unemployment Experiences on Wages. *Economic Journal*, **111** (475), F585–606.

ATKIN, D. (2016). Endogenous Skill Acquisition and Export Manufacturing in Mexico. *American Economic Review*, **106** (8), 2046–85.

BANERJEE, A. and MULLAINATHAN, S. (2010). *The Shape of Temptation: Implications for the Economic Lives of the Poor*. NBER Working Papers 15973, National Bureau of Economic Research, Inc.

BARONE, G. and MOCETTI, S. (2016). *Intergenerational mobility in the very long run: Florence 1427-2011*. Temi di discussione (Economic working papers) 1060, Bank of Italy, Economic Research and International Relations Area.

Betts, J. R. and McFarland, L. L. (1995). Safe Port in a Storm: The Impact of Labor Market Conditions on Community College Enrollments. *Journal of Human Resources*, **30** (4), 741–765.

Black, D. A., McKinnish, T. G. and Sanders, S. G. (2005). Tight Labor Markets and the Demand for Education: Evidence from the Coal Boom and Bust. *ILR Review*, **59** (1), 3–16.

Black, S. E. and Devereux, P. J. (2011). *Recent Developments in Intergenerational Mobility*, Elsevier, *Handbook of Labor Economics*, vol. 4, chap. 16, pp. 1487–1541.

Bonhomme, S. and Hospido, L. (2017). The cycle of earnings inequality: evidence from spanish social security data. *The Economic Journal*.

Chabé-Ferret, B. and Gobbi, P. (2016). *Economic Uncertainty and Fertility Cycles: The case of the post WWII baby boom*. Tech. rep., Mimeo, Université Catholique de Louvain.

Charles, K. K., Hurst, E. and Notowidigdo, M. J. (2015). *Housing Booms and Busts, Labor Market Opportunities, and College Attendance*. NBER Working Papers 21587, National Bureau of Economic Research, Inc.

Chetty, R., Hendren, N., Kline, P. and Saez, E. (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States. *The Quarterly Journal of Economics*, **129** (4), 1553–1623.

Cockx, B. and Ghirelli, C. (2016). Scars of recessions in a rigid labor market. *Labour Economics*, **41** (C), 162–176.

Corak, M. (2013). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives*, **27** (3), 79–102.

Cunha, F. and Heckman, J. J. (2008). Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Journal of Human Resources*, **43** (4).

—, — and Schennach, S. M. (2010). Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Econometrica*, **78** (3), 883–931.

Dellas, H. and Sakellaris, P. (2003). On the cyclicality of schooling: theory and evidence. *Oxford Economic Papers*, **55** (1), 148–172.

Esquieu, P. and Poulet-Coulibando, P. (2003). Vers un enseignement secondaire de masse (1985-2001). *Données Sociales – La société francaise*.

FINDEISEN, S. and SACHS, D. (2016). Optimal need-based financial aid. *Mimeo, University of Mannheim/European University Institute*.

GAINI, M., LEDUC, A. and VICARD, A. (2013). School as a Shelter? School Leaving-Age and the Business Cycle in France. *Annals of Economics and Statistics*, (111-112), 251–270.

GIULIANO, P. and SPILIMBERGO, A. (2014). Growing up in a Recession. *Review of Economic Studies*, **81** (2), 787–817.

GÜELL, M., PELLIZZARI, M., PICA, G. and RODRGUEZ MORA, J. V. (2015). *Correlating Social Mobility and Economic Outcomes*. CEPR Discussion Papers 10496, C.E.P.R. Discussion Papers.

—, RODRGUEZ MORA, J. V. and TELMER, C. I. (2014). The informational content of surnames, the evolution of intergenerational mobility and assortative mating*. *The Review of Economic Studies*.

HELLERSTEIN, J. K. and MORRILL, M. S. (2011). Dads and Daughters: The Changing Impact of Fathers on Womens Occupational Choices. *Journal of Human Resources*, **46** (2), 333–372.

HUTTUNEN, K. and RIUKULA, K. (2017). Parental job loss and childrens schooling choices. *Mimeo, Aalto University*.

INOUE, A. and SOLON, G. (2010). Two-Sample Instrumental Variables Estimators. *The Review of Economics and Statistics*, **92** (3), 557–561.

KRAMARZ, F. and SKANS, O. N. (2014). When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies*, **81** (3), 1164–1200.

LEE, C.-I. and SOLON, G. (2009). Trends in Intergenerational Income Mobility. *The Review of Economics and Statistics*, **91** (4), 766–772.

MACLEAN, J. C. (2013). The health effects of leaving school in a bad economy. *Journal of Health Economics*, **32** (5), 951–964.

MAIER, S. and VUJIĆ, S. (2017). Safe ports for all? schooling responses to jobless times in europe. *Mimeo, University of Antwerp*.

MÉNDEZ, F. and SEPÚLVEDA, F. (2012). The cyclicality of skill acquisition: evidence from panel data. *American Economic Journal: Macroeconomics*, **4** (3), 128–152.

NYBOM, M. and STUHLER, J. (2016). Heterogeneous income profiles and lifecycle bias in intergenerational mobility estimation. *Journal of Human Resources*, **51** (1), 239–268.

OECD (2016). *PISA 2015*. Pisa in focus, OECD Publishing.

OLIVETTI, C. and PASERMAN, M. D. (2015). In the name of the son (and the daughter): Intergenerational mobility in the united states, 1850-1940. *American Economic Review*, **105** (8), 2695–2724.

OREOPOULOS, P., PAGE, M. and STEVENS, A. H. (2008). The Intergenerational Effects of Worker Displacement. *Journal of Labor Economics*, **26** (3), 455–483.

— and PAGE, M. E. (2006). The Intergenerational Effects of Compulsory Schooling. *Journal of Labor Economics*, **24** (4), 729–760.

—, VON WACHTER, T. and HEISZ, A. (2012). The Short- and Long-Term Career Effects of Graduating in a Recession. *American Economic Journal: Applied Economics*, **4** (1), 1–29.

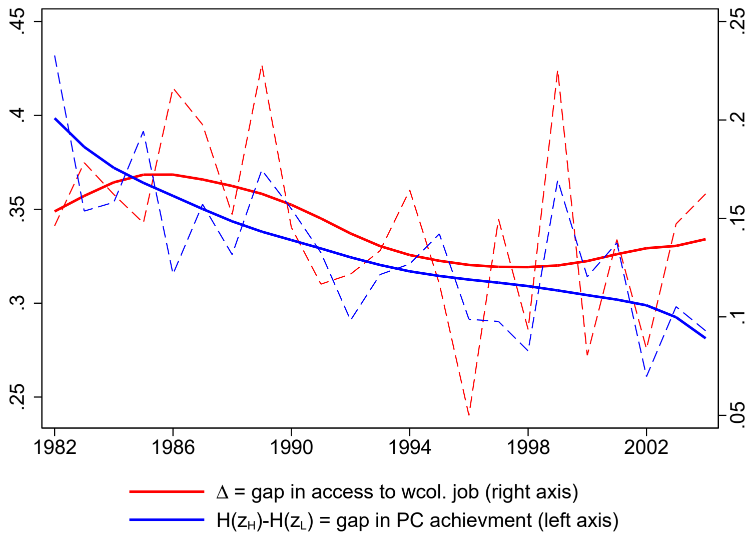
PEKKARINEN, T., UUSITALO, R. and KERR, S. (2009). School tracking and intergenerational income mobility: Evidence from the Finnish comprehensive school reform. *Journal of Public Economics*, **93** (7-8), 965–973.

SOLON, G. (1999). Intergenerational mobility in the labor market. In O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, vol. 3, Part A, *29*, 1st edn., Elsevier, pp. 1761–1800.

TANAKA, T., CAMERER, C. F. and NGUYEN, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review*, **100** (1), 557–71.

Appendix

Figure A1: Achievement Gap over time



Notes: Thin dash lines represent the cohort specific achievement gap. The thick line corresponds to a smooth series using local weighted regression (lowess) with respect to cohort year.

Table A1: Educational attainment and departmental unemployment rate at 16/18

	(1) PostComp	(2) College
BP UR at age 16 × *HighPB*	-0.426***	
	(0.143)	
BP UR at age 18 × *HighPB*		-0.389***
		(0.147)
Adjusted R^2	0.053	0.159
Dept × PB FE	✓	✓
Dept × Cohort FE	✓	✓
Dépt by PB trend	✓	✓
Mean Gap in Outcome	14.2 pp	36.7 pp
$\widehat{\beta} \times \frac{SD}{\text{gap}}$	-8.4%	-3.2%
Observations	198046	195200

Notes: Robust standard errors in parentheses – clustered at the département × white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Occupational status and departmental unemployment rate at 18

	(1) White Collar	(2) White Collar	(3) White Collar
$U^{bpl}_{18,d}$	-0.224		
	(0.234)		
$U^{bpl}_{18,d} \times$ High PB	-0.476**	-0.641***	-0.521***
	(0.221)	(0.194)	(0.186)
Adjusted R^2	0.123	0.130	0.130
Dept × PB FE	✓	✓	✓
Cohort FE	✓	✓	
Cohort × Dept FE			✓
Age × PB FE		✓	✓
Cohort × Survey FE		✓	✓
Mean Gap in Outcome	34.7 pp	34.7 pp	34.7 pp
$\widehat{\beta} \times \frac{\Delta U^{75}_{25}}{\text{gap}}$	-4.100%	-5.5%	-4.5%
Observations	195242	195242	195238

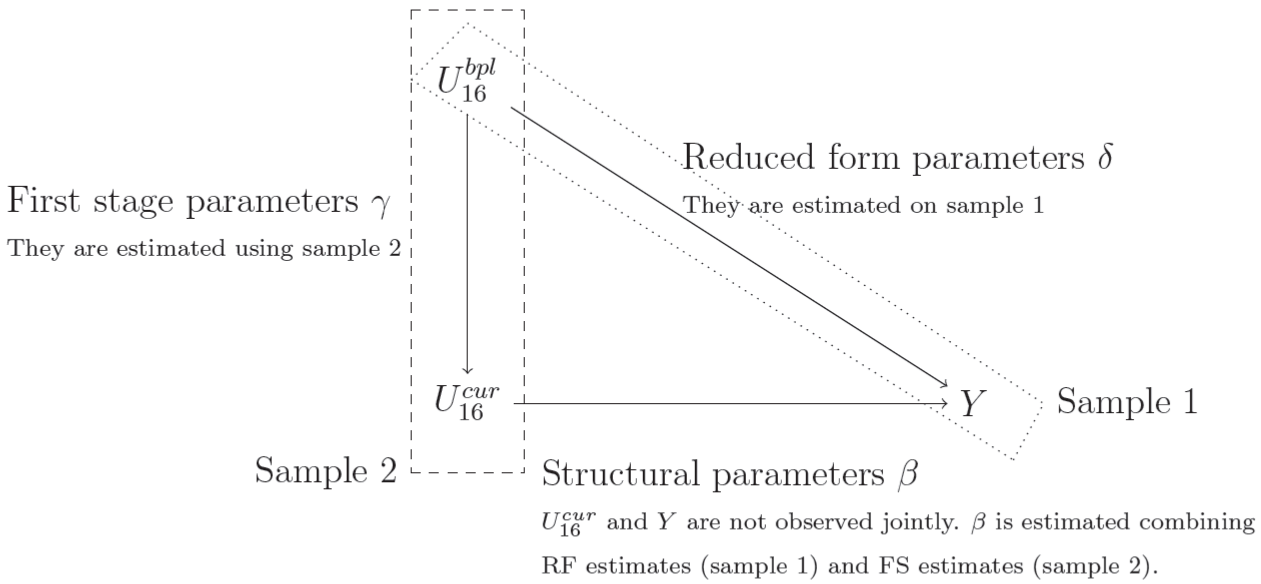
Notes: Robust standard errors in parentheses – clustered at the département × white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Occupational status and departmental unemployment rate at 16/18

	(1) White Collar	(2) White Collar
$U^{bpl}_{16,d} \times$ High PB	-0.547***	
	(0.166)	
$U^{bpl}_{18,d} \times$ High PB		-0.454**
		(0.179)
Adjusted R^2	0.130	0.130
Dept × PB FE	✓	✓
Cohort × Dept FE	✓	✓
Age × PB FE	✓	✓
Cohort × Survey FE	✓	✓
Dépt by PB trend	✓	✓
Mean Gap in Outcome	34.7 pp	34.7 pp
$\widehat{\beta} \times \frac{\Delta U^{75}_{25}}{\text{gap}}$	-4.4%	-3.9%
Observations	198092	195238

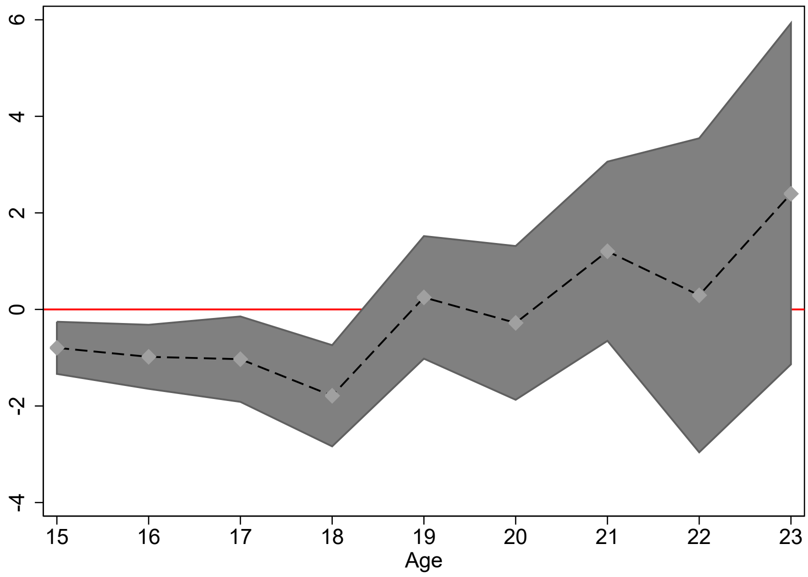
Notes: Robust standard errors in parentheses – clustered at the département × white collar father level. All regressions control for gender.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A2: Illustration of the Two-Sample 2SLS estimation



Notes: Sample 1 includes individuals above 25 at the time of survey. Sample 2 includes individuals who are 16 at the time of survey from the same cohorts as sample 1. We observe birth place for both samples – and therefore deduce unemployment at age 16 in birthplace. However, we observe long-term outcomes (highest degree, occupation) for sample 1 only and we observe current location at age 16 for sample 2 only.

Figure A3: The differential effect of local unemployment rate on subsequent training for different ages conditional on being enrolled at time t



Note: Each dot corresponds to a distinct IV regression of a binary variable for training at $t+1$ on the interaction between unemployment and parental background, for individuals of given age which is displayed in the x-axis. The second stage of the 2SLS estimation is given by equation (2S) – in footnote 14. Controls include gender and cohort as well as département $\times$ parental background fixed-effects. Local unemployment rate is instrumented by birth place unemployment rate. Shaded area correspond to 95% confidence intervals constructed using "parental background $\times$ département of birth" clustered standard errors. Unlike in results displayed in Figure 4 and Table 11, we restrict to individual enrolled in full-time education at time t.