Countercyclical School Attainment and Intergenerational Mobility

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Abstract

We study how economic conditions at the time of choosing post-compulsory education affect intergenerational mobility. Exploiting variation in the unemployment rate in individuals' birthplace 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 these cohorts are also more occupationally mobile – blue collar children are relatively more likely to become white collar when adult; and that a large fraction of this effect is explained by differences in educational attainment. Using a Two-Sample 2SLS approach, we show that accounting for differential spatial mobility between birth and age 16 by parental background results in stronger relative counter-cyclicality of long-run schooling attainment for children of blue collar fathers and occupational mobility. We provide auxiliary evidence showing that individuals experiencing local high unemployment at age 16 are more likely to be in training at age 17 and that this effect is significantly stronger for children of blue collar workers. Finally, we develop a conceptual framework that will allow us to decompose the estimated effects into differences in the effect of the cycle and in the density of students at the margin by parental background.

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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,

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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 counter-cyclical, 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.

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 – a measure that is widely seen as a measure of equality of opportunity –, since skill acquisition is one of the main channels for the transmission of economic advantage across generations (Solon, 1999). We address this question using 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 adults' 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 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.[1]

We estimate the effect of economic conditions at the time of choosing post-compulsory education on schooling attainment by parental background – educational intergenerational mobility; and how such changes translate into occupational intergenerational mobility once in the labor market. 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 – high vs. low skilled employment –, and is strongly correlated with contemporaneous earnings and educational attainment.

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 dependent on having a white-collar father. Moreover, we find that this pays off in the labor market, since we find that these cohorts are also more occupationally mobile, meaning that their probability of obtaining a white-collar job is less dependent on having a white-collar father. Finally, we find that a large fraction of this difference in occupational mobility is explained by differences in educational attainment, which is consistent with our first finding. Hence, our results suggest that although recessions tend to increase inequality due 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 region, 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).

To complement and interpret our results, we provide auxiliary evidence showing 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

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[1]The literature using aggregate unemployment is indeed subject to the criticism that national unemployment rate might be correlated with nation-wide reforms. As highlighted by Gaini *et al.* (2013), this issue is particularly salient in the French case during the period analyzed.

at age 22 where all individuals are very countercyclical in their training decision but high background individual significantly more so. We also show that differential mobility between birth and age 16 by parental background in response to unemployment is unlikely to explain our findings and if anything, when taken into account through the use of a Two-Sample 2SLS estimation (Angrist and Krueger, 1992; Inoue and Solon, 2010), increases the extent to which low parental background students are more countercyclical than students with high-parental background. Overall our results on school enrollment, school attainment and occupational mobility are consistent with scenario whereby all students' future attainment conditional on being enrolled are negatively affected by unemployment, low parental background students are more countercyclically reactive to unemployment in their post-compulsory enrollment decision which allows them to, on average, reach higher level of occupational mobility relative to high parental background students – whose post-compulsory enrollment is acyclical and post-compulsory school attainment is slightly procyclical.

We frame our analysis and interpret the findings using a one-factor model of selection into education, that delivers a closed form expression for the parameter we estimate, which is a weighted average of the differential effect of the business cycle on the costs – both direct and of opportunity – of schooling across children of high and low skilled parents and of the differential density of students at the margin by parental background. Our next step (not in this version of the paper, unfortunately, yet) will be to estimate this density to understand how important it is in driving the results, compared to the difference of the individual reaction. This is important to understand under what conditions we would expect our results to hold.

An increasing body of evidence highlights that adverse economic shocks at early stages of individuals' lives can have persistent effects on individual labor market outcomes, health or even preferences (e.g. Giuliano and Spilimbergo, 2014). Most relevant to us are the well documented wage losses entailed by entering the labor market in a recession (Oreopoulos *et al.*, 2012; Altonji *et al.*, 2016; Cockx and Ghirelli, 2016) and worse health outcomes (Maclean (2013)). 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

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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.

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. Recent papers have empirically examined the geography of inter-generational mobility (Chetty *et al.*, 2014); its evolution over time (Barone and Mocetti, 2016; Olivetti and Paserman, 2015; Güell *et al.*, 2014; Lee and Solon, 2009; Aaronson and Mazumder, 2008); the role of women's rising labor force participation (Hellerstein and Morrill, 2011); the role of the education system (Pekkarinen *et al.* (2009), Oreopoulos and Page (2006)); the effect of worker displacement (Oreopoulos *et al.*, 2008); and the correlation of mobility measures with economic and social outcomes (Güell *et al.*, 2015).[2]

Our paper is 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)). 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 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.

Finally 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).[3] Our results show that the contribution of the educational system for social mobility depends not only on how socially biased it is against enrolled

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[2]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

[3]See for instance NYT, "The Strangehold on French Schools" 09/11/2015

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students but also on access. In the French case, the low cost of post-compulsory schooling contributes very likely to explain the strongly countercyclical enrollment responses that we document by 16 year old with low parental-background thus sheltering somewhat against business cycle variations.

The paper is structured as follow. In section 2, we start by presenting a simple model of education decision where children of white- and blue-collar workers are differing in terms of unobserved ability and returns to education and are differently affected by changes in the business cycles. We then provide some institutional background, present the data and some descriptive statistics in section 3. We present the main empirical specification in section 4 and discuss various identification issues. We present the main results in section 5. We go on to discuss different channels underpinning the results, assess their robustness and provide auxiliary evidence in section 6. Finally, we conclude.

2   Conceptual framework

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:

$$log(w^N) = \alpha_0 + \alpha_1 z; \quad log(w^E) = \delta_0 + \delta_1 z$$

Where w^N and w^E stand for wages of Non-educated and Educated individuals, respectively. $\delta_0 > \alpha_0 > 0$, meaning that education has an unconditional positive effect on earnings; and $\delta_1 > \alpha_1 > 0$, meaning that education and ability are complements, and high-ability individuals are positively selected into education. An individual obtains education if it maximizes her income, net of the costs of schooling c:

$$\delta_0 + \delta_1 z - c > \alpha_0 + \alpha_1 z$$

Where the cost of schooling c includes both direct costs and foregone earnings during the time spent at school, weighted by the individuals' discount rate. All individuals of type $z \geq z^*$ obtain education, where:

$$z^* \equiv \frac{\alpha_0 - \delta_0 + c}{\delta_1 - \alpha_1} = \frac{c}{\delta_1 - \alpha_1} - \eta$$

Where $\eta = \frac{\delta_0 - \alpha_0}{\delta_1 - \alpha_1}$ 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 Ed as:

$$P(Ed) = 1 - \Phi\left(\frac{-\mu}{\sigma} - \frac{1}{\sigma}\left(\eta - \frac{c}{\delta_1 - \alpha_1}\right)\right) = \Phi\left(\frac{\mu}{\sigma} + \frac{1}{\sigma}\left(\eta - \frac{c}{\delta_1 - \alpha_1}\right)\right)$$

The business cycle affects the schooling decision in the following way:

$$\frac{\partial E[Ed|BC]}{\partial BC} = -\phi\left(\frac{\mu}{\sigma} + \frac{1}{\sigma}\left(\eta - \frac{c}{\delta_1 - \alpha_1}\right)\right)\frac{\partial c}{\partial BC}\frac{1}{\sigma}\frac{1}{(\delta_1 - \alpha_1)}$$

Consider the distribution of z within two levels of parental background $s \in (High, Low)$: $z_s \sim N(\mu_s, \sigma^2)$, where $\mu_H > \mu_L$, possibly due to genetic persistence, where we allow for full parameter heterogeneity by parental background. Let $E[Ed|s]$ denote the probability of obtaining education conditional on the parental background category s.

$$\frac{\partial E[Ed|BC,s]}{\partial BC} = -\phi\left(\frac{\mu_s}{\sigma} + \frac{1}{\sigma}\left(\eta_s - \frac{c}{\delta_{1,s} - \alpha_{1,s}}\right)\right)\frac{\partial c}{\partial BC}\frac{1}{\sigma}\frac{1}{\delta_{1,s}\alpha_{1,s}} = -\frac{\phi(\omega_s)}{\sigma}\frac{\partial c}{\partial BC}\frac{1}{(\delta_{1,s} - \alpha_{1,s})}$$

We are interested in:

$$\left[\frac{\partial E[Ed|BC,H]}{\partial BC}\right] - \left[\frac{\partial E[E|BC,L]}{\partial BC}\right] =$$

$$-\frac{1}{\sigma}\phi(\omega_h(BC))\frac{\partial c_H}{\partial BC}\frac{1}{\delta_{1H} - \alpha_{1H}} + \frac{1}{\sigma}\phi(\omega_L(BC))\frac{\partial c_L}{\partial BC}\frac{1}{\delta_{1,L} - \alpha_{1,L}} =$$

$$\frac{1}{\sigma}\phi(\omega_L(BC))\underbrace{\left[\frac{\partial c_L}{\partial BC}\frac{1}{\delta_{1,L} - \alpha_{1,L}} - \frac{\partial c_H}{\partial BC}\frac{1}{\delta_{1,H} - \alpha_{1,H}}\right]}_{\substack{\text{Difference in the effect of the cycle} \\ \text{on the margin}}} + \frac{1}{\sigma}\underbrace{\left[\phi(\omega_l(BC)) - \phi(\omega_h(BC))\right]}_{\substack{\text{Difference in density} \\ \text{at the margin}}}\frac{\partial c_H}{\partial BC}\frac{1}{\delta_{1H} - \alpha_{1H}}$$

Which means that the effect of the business cycle on educational mobility depends on two factors. The first one is the differential effect of the business cycle on the threshold above which obtaining education is optimal by parental background. To see why this might

be different, consider the following cost function, which is the sum of the foregone wages while at school $ln(\tilde{w})$ and the tuition fees $\tau(1 - FI)$ not covered by family income FI, weighted by the discount rate β.

$$c_s = \frac{ln(\tilde{w}) + \tau(1 - FamilyIncome_s)}{\beta}$$

$$\frac{\partial c_s}{\partial BC}\frac{1}{\delta_{1,s} - \alpha_{1,s}} = \frac{\partial}{\partial BC}\left(\frac{ln(\tilde{w}) + \tau(1 - FamilyIncome_s)}{\beta_s}\right)\frac{1}{\delta_{1,s} - \alpha_{1,s}}$$

Where, to simplify, we assume that the first wage out of school $ln(\tilde{w})$ does not depend on ability. What are the sources of heterogeneity in the effect of the business cycle on the cost of schooling? The effect of the business cycle on the opportunity costs of schooling $ln(\tilde{w})$ is weighted by $\beta_s(\delta_{1,s} - \alpha_{1,s})$. If children of lower income families have lower discount rates (Tanaka *et al.* (2010), Banerjee and Mullainathan (2010)), or larger returns to education, due to complementarities with early parental investments, the effect will be larger for them. At the same time, they are more likely to suffer family income losses due to the skill-biased nature of unemployment (Hoynes *et al.*, 2012). Hence, in general, the sign of the differential effect of the cycle on the overall cost of education will be ambiguous.

The second factor driving the effect of the business cycle on educational mobility is the difference, by parental background, in the density of students at the margin: $[\phi(\omega_h(BC)) - \phi(\omega_l(BC))]$. This might be different depending on the type of education (any post-compulsory vs. college). In the case of post-compulsory schooling, those with low-skilled parents are less likely to obtain it, but also for them it is widespread (i.e., above 50% in most cases), and hence we would expect this term to be negative. In the case of college degrees, although there is a parental background gap in attainment as well, the sign of this terms is less predictable, since in some départements and cohorts the fraction of students with a college degree is below 50%.

3   Data

We use the French Labor Force Survey, from 1990 to 2014, merged with national and départemental unemployment data from 1982 to 2014.[4]. We keep all individuals older than 25 at the time of the survey; and for which we have information on the unemployment

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[4]From 1990 to 2002, the LFS is yearly, from 2003 onwards, it is quarterly

rate at the time of choosing schooling (i.e., those born between 1965 and 1988). We obtain a sample of slightly more than 180000 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.[5]

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 interchangeably. The descriptives show that white collars are more likely to hold post-compulsory degrees; and much more likely to hold college degrees. Moreover, they are twice as likely to have a white-collar father, meaning that there is a lot of persistence. More than half of the white collar workers had 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, they are twice as likely to be employed as a white collar worker: two thirds of white collar children end up in white collar occupations. 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. Overall, the descriptives suggest that our binary measure of economic status is a meaningful measure.

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[5]In particular, blue collars are ouvriers and employes, and white collars are professions intermediaires and cadres

Table 1: Occupation measure and covariates

	All	Blue Collar	White Collar
Post Compulsory Education	0.832	0.736	0.955
	(0.374)	(0.441)	(0.207)
University Degree	0.394	0.142	0.720
	(0.489)	(0.349)	(0.449)
White Collar Father	0.357	0.215	0.540
	(0.479)	(0.411)	(0.498)
Unemployment rate at age 16	8.793	8.751	8.847
	(1.043)	(1.036)	(1.049)
Observations	181418	102316	79102

Standard deviation in parenthesis

Table 2: Parental Occupation measure and covariates

	All	Blue Collar Father	White Collar Father
Post Compulsory Education	0.832	0.780	0.925
	(0.374)	(0.414)	(0.264)
University Degree	0.394	0.263	0.631
	(0.489)	(0.440)	(0.483)
White Collar	0.436	0.312	0.660
	(0.496)	(0.463)	(0.474)
Unemployment rate at age 16	8.793	8.763	8.847
	(1.043)	(1.039)	(1.048)
Observations	181418	116679	64739

Standard deviation in parenthesis

4 Empirical specification

Our baseline specification is the following:

$$\text{Outcome}_i = \beta_0 + \beta_1 \text{White Collar father}_i + \beta_2 U_{16,i}^{bpl}$$
$$+ \beta_3 (U_{16}^{bpl} \times \text{White Collar father})_i + \beta_4 X_i + \epsilon_i \tag{1}$$

where U_{16}^{bpl} refers to the unemployment rate prevailing in the département of birth of individual i when she was 16.

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 national economic conditions, then we exploit 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 region, 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

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parental background (Lee and Solon, 2009). All regressions are estimated by OLS, include a gender dummy as a control, and standard errors are clustered at the parental skill by département level.

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 recession are more intergenerationally mobile. Including year of birth fixed effects and département by parental skill fixed effects does not significantly change the results. This estimates suggest that being exposed to a national unemployment rate that is one point higher at the moment of choosing post-compulsory education reduces the average parental background gap in post-compulsory attainment by slightly more than 10%.[6]

Table 4 reports estimates of the same relationship, but exploiting variation in economic conditions at the département level. This regressions include year of birth fixed effects, and département by parental skill fixed effects, département by year of birth fixed effects and département by parental skill trends. This means that these estimates exploit variation net of unobserved characteristics for every cohort in every département, and net of unobserved characteristics and trends by every skill group in every département. The point estimates in table 4 suggest that being exposed to a regional unemployment rate that is one point higher at the moment of choosing post-compulsory education reduces the parental background gap in post-compulsory attainment by between 3% and 9%.

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

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[6]The average parental background gap is 0.145, as shown in table 1

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

	(1) Post Compulsory	(2) Post Compulsory	(3) Post Compulsory
National Unemployment at 16	0.0308*** (0.00109)		
White Collar father	0.289*** (0.0129)	0.279*** (0.0155)	
Nat.Unemp* White Collar father	-0.0170*** (0.00142)	-0.0164*** (0.00161)	-0.0164*** (0.00165)
Dépt FE		✓	
Year of birth FE		✓	✓
Dépt × Parental Skill FE			✓
N	198063	198063	198063

Robust standard errors in parentheses – clustered at the cohort × département level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	(1) Post Compulsory	(2) Post Compulsory	(3) Post Compulsory
Dept Unemployment at 16	0.00568*** (0.00163)		
Dept.Unemp*White Collar father	-0.0130*** (0.00141)	-0.0121*** (0.000962)	-0.00426*** (0.00143)
Dépt × Parent Skill FE	✓	✓	✓
Year of birth FE	✓		
Dépt × Year of birth FE		✓	✓
Dépt × Parental Skill Trends			✓
N	198063	198046	198046

Robust standard errors in parentheses – clustered at the cohort × département level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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. However, again, the 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 regional unemployment rate that is one point higher at the typical moment of choosing college education reduces the parental background gap in college degree attainment by between 1% and 1.5%.

Table 5: Higher education and departmental unemployment rate at 18

	(1) College	(2) College	(3) College
Dept Unemployment at 18	-0.00384*		
	(0.00207)		
Dept.Unemp*White Collar father	-0.00560**	-0.00516***	-0.00397***
	(0.00219)	(0.00148)	(0.00144)
Dépt × Parent Skill FE	✓	✓	✓
Year of birth FE	✓		
Dépt × Year of birth FE		✓	✓
Dépt × Parental Skill Trends			✓
N	192708	192706	192706

Robust standard errors in parentheses – clustered at the cohort × département level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, these results suggest that children of low skilled parents are significantly more counter-cyclical than children of high skilled parents. This implies that cohorts exposed to bad economic conditions at the moment of making important educational choices are more intergenerationally educationally mobile. An interesting question is whether this extra schooling induced by the business cycle is productive and whether it translates into intergenerational occupational mobility, defined as the probability of having a white collar job conditional on having a white collar father.

5.2 Occupational mobility

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 would lower the return to schooling for the whole cohort, which could reinforce the effect on educational mobility and lead to increased occupational mobility.[7].

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 national unemployment rate that is one point higher at the moment of choosing post-compulsory education reduces the intergenerational elasticity in white collar employment by around 1.7%.

Table 6: Occupation and national unemployment rate at 16

	(1) High Skilled	(2) High Skilled	(3) High Skilled	(4) High Skilled
National Unemployment at 16	0.0168*** (0.00126)			
White Collar father	0.388*** (0.0187)			
Nat.Unemp*White Collar father	-0.00481** (0.00210)	-0.00621** (0.00260)	-0.00606** (0.00246)	-0.00595** (0.00245)
Age × Parental Skill FE		✓	✓	✓
Survey year × birth year FE		✓	✓	✓
Dépt FE			✓	
Dépt × Parental Skill FE				✓
N	198109	198109	198109	198109

Robust standard errors in parentheses – clustered at the cohort × département level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 reports estimates of the same relationship, but exploiting variation in départemental

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

economic conditions. The results are stable across specifications and have similar implications. The point estimates in table 7 suggest that being exposed to a départemental unemployment rate that is one point higher at the moment of choosing post-compulsory education reduces the intergenerational elasticity in white collar employment by around 1.7%.

Table 7: Occupation and departmental unemployment rate at 16

	(1) High Skilled	(2) High Skilled	(3) High Skilled
Dépt.Unemp at 16	-0.0000342		
	(0.00214)		
Dépt.Unemp at 16*White Collar father	-0.00576***	-0.00540***	-0.00547***
	(0.00207)	(0.00146)	(0.00166)
Age × Parental Skill FE	✓	✓	✓
Survey year × birth year FE	✓	✓	✓
Dépt × Parental Skill FE	✓	✓	✓
Dépt × birth year FE		✓	✓
Dépt × Parental Skill Trends			✓
N	198109	198092	198092

Robust standard errors in parentheses – clustered at the cohort × département level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 reports estimates of the same relationship, but exploiting variation in départemental economic conditions at the moment of choosing college, at age 18. The results are stable across specifications, and have similar implications. The point estimates in table 8 suggest that being exposed to a départemental unemployment rate that is one point higher at the typical moment of choosing to enrol into college reduces the intergenerational elasticity in white collar employment by around 1.4%.

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. Over more than twenty years, both nationally and within départements, the difference between the highest and the lowest level of unemployment is of around 4 points, which would imply a change in the white-collar elasticity of 6.8%. 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.

Table 8: Occupation and departmental unemployment rate at 18

	(1) High Skilled	(2) High Skilled	(3) High Skilled
Dépt.Unemp at 18	-0.00187		
	(0.00254)		
Dépt.Unemp at 18*White Collar father	-0.00563**	-0.00505**	-0.00442**
	(0.00236)	(0.00195)	(0.00192)
Age × Parental Skill FE	✓	✓	✓
Survey year × birth year FE	✓	✓	✓
Dépt × Parental Skill FE	✓	✓	✓
Dépt × birth year FE		✓	✓
Dépt × Parental Skill Trends			✓
N	192743	192741	192741

Robust standard errors in parentheses – clustered at the cohort × département level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Channels and robustness

6.1 Educational attainment and occupational mobility

The previous results are consistent with increased intergenerational mobility in education leading to an increased intergenerational mobility in labor market outcomes. Hence, we would expect our estimates of the effect of the business cycle on occupational mobility to change substantially after controlling for educational attainment. Of course, this 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 9 and 10 report intergenerational occupational mobility regressions, controlling for educational attainment. We can see how change in educational attainment explain most of the effect of the cycle on mobility, that becomes close to zero and not significant, which is consistent with our proposed mechanism.

6.2 Accounting for spatial mobility between birth and age 16

Using birthplace unemployment rate is useful in several ways. Exploiting cross-sectional variation in local variation allows us to control flexibly for aggregate trends in school attainment by including cohort fixed-effects. Using birthplace unemployment rules out geographical sorting based on economic conditions. However it would be useful to assess the strength of the association between birthplace and location at 16 unemployment rate. Examining whether this relationship varies by parental background could also allow us to make sure the

Table 9: Occupation and departmental unemployment rate at 16

	(1) Post Compulsory	(2) High Skilled	(3) High Skilled
Dépt.Unemp at 16*WhiteColFath	-0.0128***	-0.00540***	-0.00144
	(0.00110)	(0.00146)	(0.00150)
Post Compulsory Education			0.310***
			(0.00666)
Age × Parental Skill FE	✓	✓	✓
Survey year × birth year FE	✓	✓	✓
Dépt × Parental Skill FE	✓	✓	✓
Dépt × birth year FE	✓	✓	✓
N	198046	198092	198046

Robust standard errors in parentheses – clustered at the cohort × département level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Occupation and departmental unemployment rate at 18

	(1) College	(2) High Skilled	(3) High Skilled
Dépt.Unemp at 18*WhiteColFath	-0.00573***	-0.00505**	-0.00195
	(0.00149)	(0.00195)	(0.00175)
College			0.549***
			(0.00525)
Age × Parental Skill FE	✓	✓	✓
Survey year × birth year FE	✓	✓	✓
Dépt × Parental Skill FE	✓	✓	✓
Dépt × birth year FE	✓	✓	✓
N	192706	192741	192706

Robust standard errors in parentheses – clustered at the cohort × département level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

differential impact of birthplace unemployment rate on educational decisions is not driven by differential geographical mobility by parental background.

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. Notably we see how this relationship varies by parental background. In a second time, we take note of the somewhat differential pattern of mobility and account for it in our main estimation by using a Two-Sample 2SLS estimator.

Descriptive evidence

Notice that in our estimation sample we focus on individuals 25 or older at the time of the survey interview and we do not know their location at age 16. We can however examine the relationship between birthplace and location at 16 unemployment rates 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 (i) how strong this relationship is, (ii) to which extent it varies overtime, (iii) to which extent it varies with parental background.

To this aim, figures 1 2 and 3 display cohort specific coefficients and cohort × parental background specific coefficients from the regression:

$$U_{16,i}^{cur} = \alpha + \beta U_{16,i}^{bpl} + \delta X_i + \varepsilon_i$$

where U_{16}^{cur} and U_{16}^{bpl} refer to local unemployment rate respectively in the département of birth and of current resident at age 16. The coefficients are remarkably stable over time. Moreover they are rather similar across family background suggesting that the differential impact of the birthplace unemployment rate at age 16 on educational attainment is unlikely to reflect differential geographical mobility across parental background. To investigate this more formally we now proceed to an instrumental estimation whereby we instrument place of residence rate by birthplace unemployment at age 16.[8]

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[8]In the Subsection 6.3, we investigate this issue by focusing on different sample 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 figures 2 and 3.

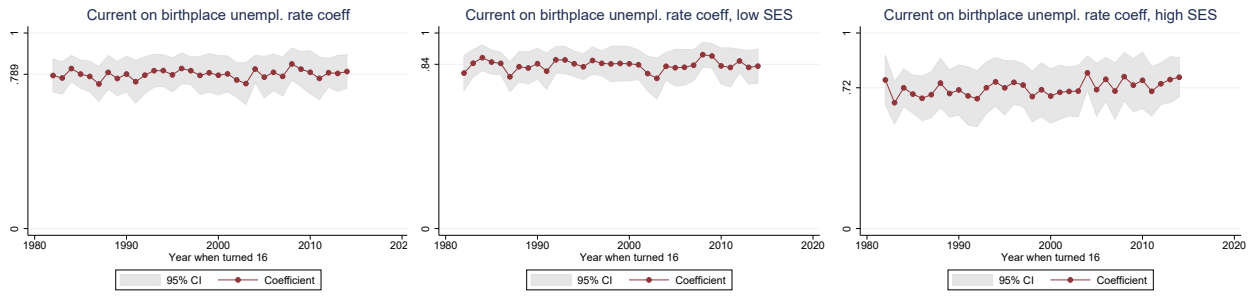Relationship between birth place and residence at 16 unemployment rate for different cohorts

| Figure 1: All individuals | Figure 2: Low skill parents | Figure 3: High skill parents |

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 observed 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 27 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 place of residence at age 16 as well as 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 6 displays the logic of the estimation. Results are displayed in Table 11.

Table 11: Two-Sample 2SLS estimates of the effect of departmental unemployment rate at 16 on post Compulsory and Occupational

	(1)	(2)
	Post Compulsory	High Skilled
Dépt.Unemp at 16	0.008	-0.00638
	(0.00110)	(0.006263)
Dépt.Unemp at 16*WhiteColFath	-0.0249***	-0.0108***
	(0.00273)	(0.00393)
Age × Parental Skill FE	✓	✓
Dépt × Parental Skill FE	✓	✓
Survey year × birth year FE		✓
N	198046	198092

Robust bootstrapped standard errors are clustered at the (departement × cohort) level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 present two advantages. It allows to have a larger sample size than if we had focused on the 16 year old, as HEA is documented for individuals of all ages. More importantly, it allows us to look at longer run outcomes by examining the occupational status of individuals who are well into their working lives – we focus on individuals aged 27 or more.[9]

An alternative, and in many ways complementary, approach to analyse the impact of the business cycle on schooling would be to investigate the impact of local unemployment at age 16 on the likelihood of being in training or not at age 17. This analysis is possible 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 our finding of countercyclical schooling attainment is corroborated by the fact 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.[10] We estimate the

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[9]Moreover, the highest degree obtained is a rather unambiguous concept and a salient event in one's lifetime, therefore it seems unlike to subject to very much recall bias.

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

following equation:

$$T_{17,i} = \alpha + \beta_1 \cdot U_{16,i}^{bpl} + \beta_2 \cdot (U_{16}^{bpl} \times \text{White Collar father})_i + X_i'\delta + \varepsilon_i \qquad (2)$$

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.

Equation 2 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 that of 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 2, it constitutes a valid instrument for U_{16}^{cur}. [11]

Table 12: Training and departmental unemployment rate, dépt of birth, at 16

	(1)	(2)
Training at 17	RF	2SLS
Dépt.Unemp at 16	0.0098***	0.025***
	(0.002)	(0.0057)
Dépt.Unemp at 16*WhiteColFath	-0.0096***	-0.015***
	(0.0022)	(0.004)
Cohort FE	✓	✓
Dépt of birth × Parental Skill	✓	✓
1st Stage Kleibergen-Paap F		360.181
N	31302	31302

Robust standard errors clustered at the cohort × département of birth level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results in table 12 are in line with our previous findings, the IV estimates (Column 2) suggesting even a larger relative counter-cyclicality of the children of the low skilled – in

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

$$U_{16,i}^{cur} = \alpha^{FS} + \beta_1^{FS} \cdot U_{16,i}^{bpl} + \beta_2^{FS} \cdot (U_{16}^{bpl} \times \text{White Collar father})_i + X_i'\delta^{FS} + \varepsilon_i \qquad (1S)$$

$$T_{17,i} = \alpha + \beta_1 \cdot \widehat{U^{cur}}_{16,i} + \beta_2 \cdot (U_{16}^{cur} \times \widehat{\text{White Collar father}})_i + X_i'\delta + \varepsilon_i \qquad (2S)$$

line with the Two-Sample 2SLS evidence displayed in Table 11. An one-percentage point decrease in the local unemployment rate at age 16 decreases the likelihood of being in training at age 17 by 2.5 and 1 percentage point for individuals with a low or high-skill father respectively. The difference is significant at the 1% confidence level.

As a way to validate the method used, we estimate specification 2 but shifting the age at which unemployment and subsequent training are observed by one year, from age 16 to 56. If the results presented above are simply 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 for different age. On the contrary if the coefficient capture a causal relationship between unemployment and individuals' decision to enroll or remained in training, we expect individuals in their late teens and early 20s to be very reactive while we do not expect individuals in their 40, therefore we should see positive coefficients for young individuals and these coefficients should progressively decline.

The latter prediction is broadly supported by results displayed in Figure 4. Panel (A) shows the coefficients of separate regressions for children of low-skilled fathers from age 16 to 56. We see that the highest effect is associated with unemployment at age 16 and age 22 and then progressively decline to become approximately null at age 30 and beyond. Panel (B) displays the same coefficient for children of high-skilled fathers. We see that they are less reactive to local unemployment at age 16 and become most reactive around age 22 and remains highly so for age 23 and 24. Panel (C) displays the different in coefficients between children of high and low-skilled fathers. Interestingly we see that, as suggested by our previous results, that children of with high parental background are much less responsive to the local business cycle in their late teens but that the difference is reversed at age 22. This is consistent with high socio-economic status (SES)[12] individuals using higher education as a buffer in responses to local labor market conditions while low parental background individuals adjust through both post-compulsory and higher education but uses the latter to a lower extent than high parental background individuals.

Note that the large difference in estimated coefficients between blue collar and white collar children around age 22 that we observe in Panel C of Figure 4 could reflect (i) a stronger response of high parental background individuals conditional on being enrolled in training
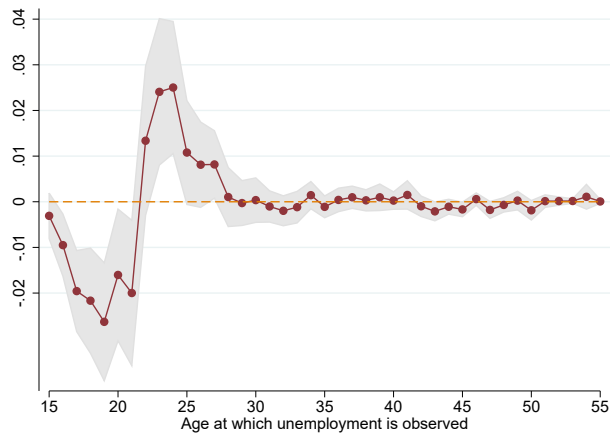
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[12]Here, we use socioeconomic status and parental background interchangeably.

Figure 4: The effect of local unemployment rate on subsequent training for different ages (15 to 55)
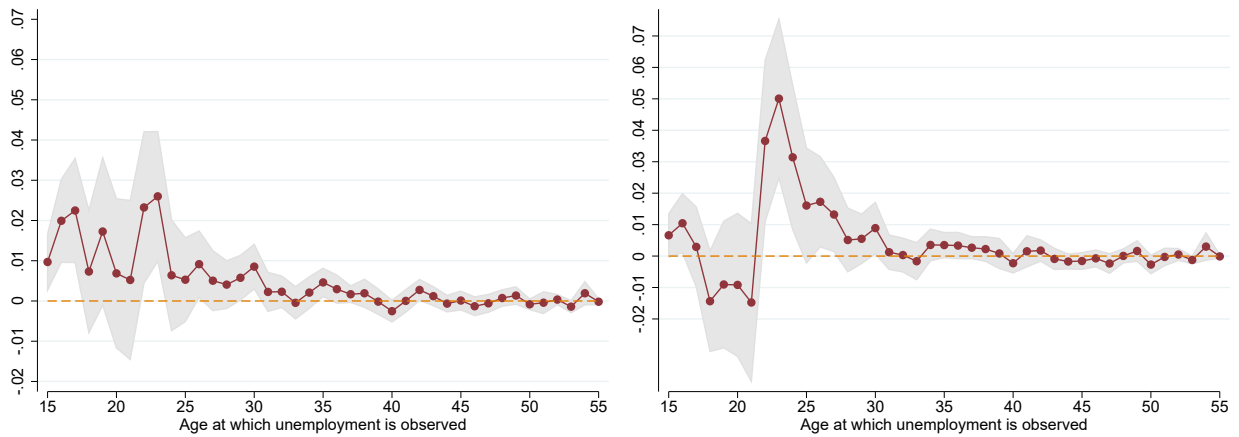
A: Low skilled parents

B: High skilled parents

C: Diff. betw. B and A

Note: Each dot corresponds to a distinct IV regression of a binary variable for training at $t+1$ on local unemployment at t and an 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 11. Controls include gender and cohort as well as département × parental background fixed-effects. Local unemployment rate is instrumented by birth place unemployment rate. Shaded area correspond to 95% confidence intervals constructed using "cohort × département of birth" clustered standard errors.

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 for individuals age 15 to 24 at time t – we run out of observations to fit our specification with département × skill cat and cohort fixed effects when considering individuals 25 or more. Results are displayed in Figure 5.

Overall these results confirm a causal effect of local unemployment on individual training decision and show that the age 16 is highly relevant for individuals whose father is a blue-collar. Along with age 22, this the age at which they are most reactive and, perhaps more importantly to understand social mobility, this is the age where they most reactive relative to children of white collar fathers.

6.4 External validity

Following our a one-factor model of selection into education, we obtained a closed expression for the parameter we estimate, which is a weighted average of the differential effect of the business cycle on the costs -both direct and of opportunity- of schooling across children of high and low skilled parents and of the differential density of students at the margin by parental background. Our next step will be to estimate this density to understand how important it is in driving the results, compared to the difference of the individual reaction. This is important to understand under what conditions we would expect our results to hold in alternative settings.

7 Conclusions

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 pays off in the labor market, 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

Figure 5: The effect of local unemployment rate at time t on subsequent training for different ages (15 to 24), **conditional on following a training in** t
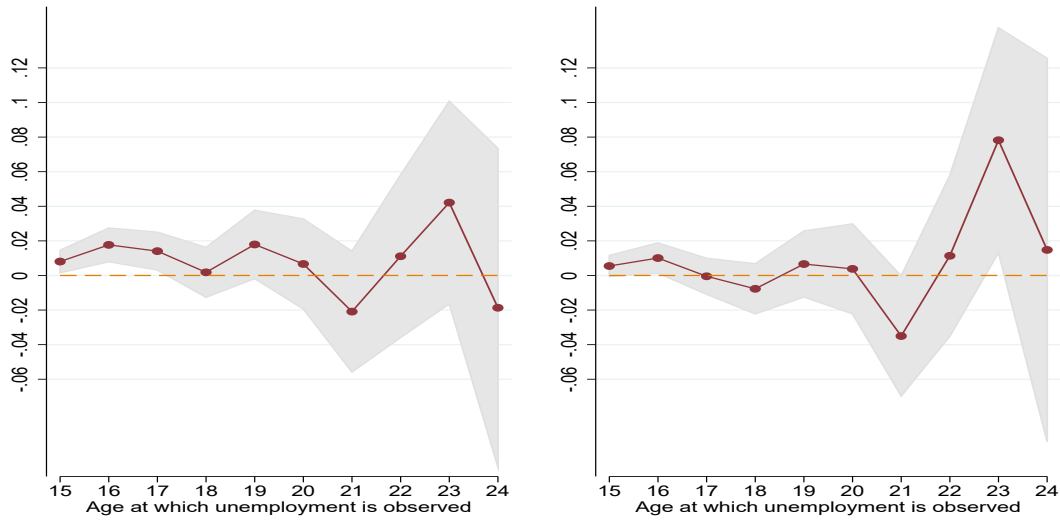
A: Low parental background; **B**: High parental background
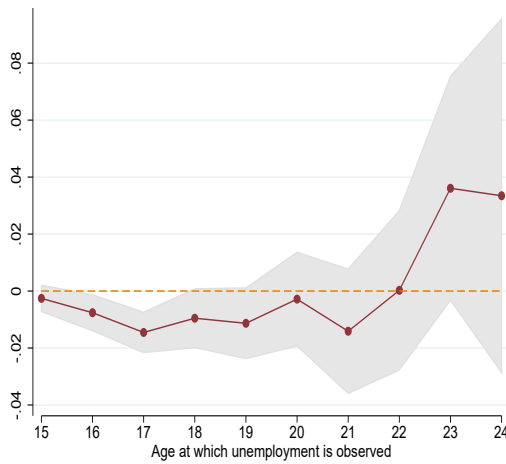
C: B - A

<u>Note</u>: Each dot corresponds to a distinct regression of training at $t+1$ on local unemployment at t and an interaction between unemployment and parental background, for individuals of given age which is displayed in the x-axis. Controls include gender and cohort as well as département × parental background fixed-effects. Local unemployment rate is instrumented by birth place unemployment rate. The second stage of the 2SLS estimation is given by equation (2S) – in footnote 11. Controls include gender and cohort as well as département × parental background fixed-effects. Local unemployment rate is instrumented by birth place unemployment rate. Shaded area correspond to 95% confidence intervals constructed using "cohort × département of birth" clustered standard errors.

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 the highest moment of the cycle, the probability of having a white collar job conditional on having a white collar father increases by 6.8%, compared to cohorts deciding in the lowest moment of the cycle (around 4 percentage points of difference in unemployment rate). Hence, our findings suggest that especially for the 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.

We use a simple selection model to interpret our estimates, to better understand in what cases we would expect our results to hold. The results could be driven by a differential effect of the business cycle on the optimal level of schooling by parental background; or by the fact that the number of students close to the margin where obtaining education becomes optimal differs by parental skill category. Our next step is to empirically disentangle these effects to understand under what conditions we would expect our results to hold.
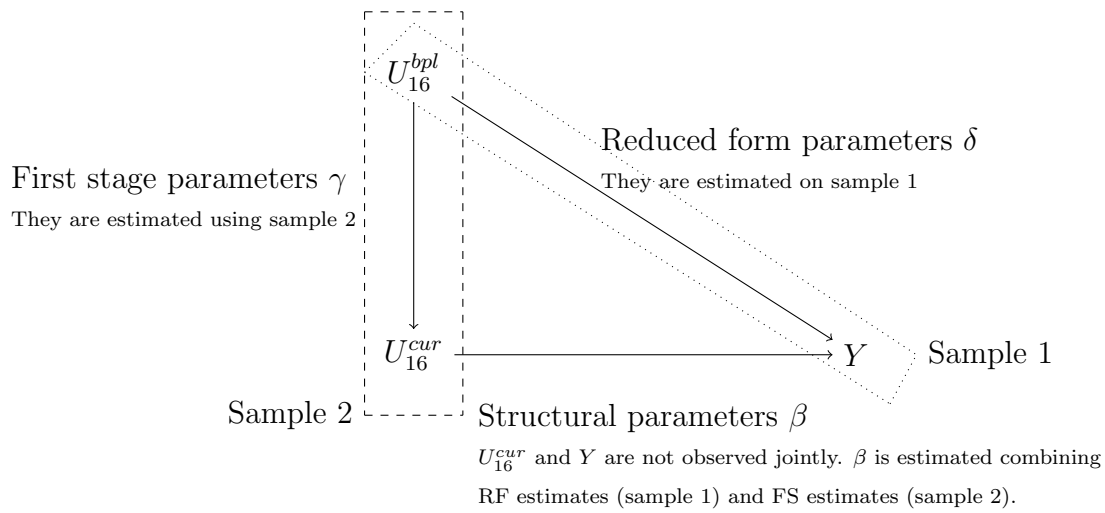
References

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.

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.

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.

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.

HOYNES, H., MILLER, D. L. and SCHALLER, J. (2012). Who Suffers during Recessions? *Journal of Economic Perspectives*, **26** (3), 27–48.

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

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.

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

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.

Figure 6: Illustration of the Two-Sample 2SLS estimation

U_{16}^{bpl}

Reduced form parameters δ

They are estimated on sample 1

First stage parameters γ

They are estimated using sample 2

U_{16}^{cur} $\longrightarrow$ Y Sample 1

Sample 2

Structural parameters β

U_{16}^{cur} and Y are not observed jointly. β is estimated combining

RF estimates (sample 1) and FS estimates (sample 2).

Notes: Sample 1 includes individuals above 27 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.