The Intergenerational (Im)mobility of Immigrants

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Abstract

This paper studies the influence of pre-migration social background on the long-term economic assimilation of immigrants. I use unique French survey data to trace family histories over three generations, before and after migration. While many immigrants experience an occupational downgrading at migration, their children benefit from the high socio-economic status their family had in the origin country. As a result, characteristics of immigrant grandparents are more predictive of their grandchildren's achievements than are characteristics of native grandparents. While immigrants cannot fully transfer their human capital between labor markets, they can transmit it across generations.

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1 Introduction

Consider the following hypothetical example: a white-collar from a high socio-economic background in a low-income country migrates to Europe. For many reasons (he does not write well in the language of the country, he cannot rely on his professional network, his degree is not officially recognized, etc.), he cannot find a similar job to the one he had before migration. He ends up working as a construction worker. In the destination country, he is indistinguishable from another immigrant construction worker who was a blue-collar worker before migration. Yet, they may be very different and their children may have different prospects in life. The objective of this paper is to investigate if this anecdotal story has empirical grounds.

To take such a long-term perspective, I use unique French survey data to trace family histories over three generations, in both the origin and destination countries, before and after migration. I use information on occupation and education of second generation immigrants (the children), their parents (who emigrated) and their grandparents (who stayed in the origin country). France has a long tradition of immigration with an estimated 40% of the French population having at least one immigrant grandparent.[1] This provides a large variety of origin countries and migration periods to study the long-term assimilation of immigrants.

Pre-migration status is key in explaining the educational outcomes of second generation immigrants. Having a father who prior to migrating had a high-skilled managerial position is associated with a 28% increase in the probability of finishing high school (conditional on father's occupation in the destination country). This effect is particularly noteworthy for immigrants with a low-type occupation (after migration). This is indicative that pre-migration background plays an important role in the upward intergenerational mobility observed in the destination country. A similar result holds for having high socioeconomic status (SES) grandparents.

[1] According to demographer Cris Beauchemin from the National Institute of Demography (INED) in charge of the survey used in this paper. See interview in https://www.la-croix.com/France/Immigration/Quelle-part-limmigration-demographie-francaise-2018-02-21-1200915395.

A “grandparent effect” (conditional on parents’ SES) has already been documented in the general population (Mare, 2011; Chan and Bolivier, 2013; Olivetti and Paserman, 2015). However, grandparent characteristics do not play the same role for immigrants and natives. Since I restrict attention to immigrant grandparents who stayed in the origin country, they did not go through skill downgrading (as many parents did when they migrated). Information about their status should be particularly informative, at least compared to information derived from parents in the destination country. Such disruption in family SES does not exist among natives; information about parents and grandparents should be more similar. Therefore, characteristics of grandparents should be (relatively) more important in predicting immigrant outcomes than they are in predicting natives’.

It is difficult to compare the importance of family background between immigrants and natives.[2] To do so, I use machine learning techniques, i.e. random forests (Breiman, 2001), which allow to compute the relative importance of each variable in terms of its predictive ability.[3] I show that the education and occupation of grandparents are more informative (with respect to occupation of the parents in the destination country) for immigrants than natives. These results are robust to using more traditional measures of goodness of fit, such as R^2 from linear regressions.

To unveil channels, I use information on the transition between labor markets (first job and professional experience in France) and parental investment in children (helping more with homework, sending their children to schools outside their neighborhood, paying for private lessons, offering better studying conditions at home). I test several mechanisms based on the idea that there is a dichotomy between what happens in the labor market and in the household; immigrants cannot entirely transfer their human capital (HC) between labor markets (in different countries) but can transmit it across generations. In the hypothetical example, the white collar became a construction worker (in the labor market) but still raises his children as a white collar would (in the household).

[2] The distribution of education levels and occupations differ substantially between countries and time periods (Xie and Killewald, 2013; Long and Ferrie, 2013), making it difficult to find a suitable benchmark.

[3] Predictive ability is measured in terms of the reduction in mean squared errors. Section 4 is devoted to explaining these methodological aspects.

The first mechanism is occupational downgrading at migration. The higher it is, the harder it is to infer parents' HC from their occupation in the destination country. Around two-thirds of immigrants who had a high-skilled managerial position find a lower-type occupation upon arrival. The second channel is parental investment. Immigrants with high pre-migration SES invest more in their children and, these investments pay off. The general picture is that the situation of immigrants follows a U-shape over time. This corresponds to a situation in which immigrants were heterogeneous before migrating, this heterogeneity is greatly reduced with the first generation and reappears with the second generation.

The first strand of literature this paper contributes to is the one on the intergenerational mobility of immigrants. Most studies (Borjas, 1993; Aydemir et al., 2009; Ward, 2020; Abramitzky et al., 2021) relate outcomes of first and second generation immigrants in the destination country. These papers control for origin country but do not include family specific information on pre-migration status. Origin country dummies may not capture well individual situations if immigrants from the same country are heterogeneous.

Recent work (Ward, 2020; Abramitzky et al., 2021) studies the long-term social mobility of immigrants in the U.S. Ward (2020) follows immigrants over three generations and finds strong persistence of grandparents' characteristics on grandchildren, stronger than predicted by a standard grandfather-grandson elasticity. Abramitzky et al. (2021) focuses on the mobility of immigrants over two generations in two different periods of U.S. history; the Age of Mass migration and the current period. They find a higher rate of upward mobility at the bottom of the earnings distribution for immigrants than for natives. I depart from these studies in that I take the situation of the family in the origin country as the relevant starting point to assess the mobility of second generation immigrants (the children). I also test mechanisms previously mentioned in the literature: skill downgrading (Borjas, 2015; Abramitzky et al., 2021) and parental investment and transmission (Becker et al., 2020).

In sociology, Ichou (2014) studies the effects of parental relative (in the origin country) education level on the decision to migrate and on the educational achievements of their children. He finds support for positive selection into migration and a positive effect of parents' relative level of education.[4] Catron (2020) studies the influence of pre-migration background on the economic success of second generation immigrants in the U.S. He links ship manifest records (which include occupation before migration) to U.S. census and finds a large effect of pre-migration status on the second generation (although lower than on outcomes of the first generation).

The second strand of literature this paper contributes to is the one on the economic assimilation of immigrants (Friedberg, 2000; Eckstein and Weiss, 2004; Cohen-Goldner and Eckstein, 2008; Caponi, 2011). Caponi (2011) develops a dynamic model where the first generation is ready to suffer a loss for the benefit of the second. The author matches survey data from the US and Mexico to estimate a structural model of immigrants' earnings. In this paper, I use data which directly follows the same families before and after migration. This allows to better apprehend the (dis)continuities brought by migration at the individual level.

Finally, this paper contributes to the general discussion on long term social mobility (Mare, 2011; Chan and Bolivier, 2013; Lindahl et al., 2015; Braun and Stuhler, 2018; Adermon et al., 2021). This literature typically finds less mobility across multiple generations than was first thought by Becker and Tomes (1986). It is an open question whether it is driven by the presence of older generations (typically grandparents) or by the transmission of latent unobservable characteristics (Clark, 2014). This paper exploits a setting in which presence of older generations does not play a role as I focus on families where grandparents did not migrate. This paper provides evidence supporting the latter explanation.

The rest of the paper is organised as follows: section 2 presents the data. Section 3 shows the results on long-term persistence. Section 4 compares grandparent effect between immigrants and natives. Section 5 tests empirically some mechanisms. Section 6 concludes.

[4]Part of this paper deals with questions not tackled in Ichou (2014), namely the loss of human capital at migration and the role of grandparents. Including them makes the link between the situations of different generations clearer. I also go beyond descriptive evidence and show through which channels family pre-migration characteristics operate.

2 Description of the data

2.1 One dataset, two samples

The dataset used in this paper is "Trajectoires et Origines" (TeO), collected by the National Institute of Demographic Studies (INED) and the National Statistical Agency (INSEE) in 2008/2009. It is a cross sectional survey (18,864 persons interviewed in total) based on representative samples of immigrants and natives. TeO has several advantages over alternative data sources such as labor force surveys and censuses. First, TeO is designed with the specific purpose of studying first and second generation immigrants; it asks questions targeted for this population. Second, TeO specifically samples 2nd generation immigrants. People do not appear as immigrants in civil registries if they are born in France. Second generation immigrants have to be sampled from registries of first generation immigrants. Last but not least, TeO contains information on the SES in the origin country.

Three different populations are surveyed in TeO: (i) first generation immigrants, (ii) second generation immigrants and (iii) natives. The questions in the survey refer to different moments in the lives of the people being interviewed: the personal and family history, the current situation and the situation of the children. I do not have to merge different data sources to gather information on different generations (Caponi, 2011; Abramitzky et al., 2014; Olivetti and Paserman, 2015; Abramitzky et al., 2021).

The sample that surveys first generation, from now on referred to as *sample first*, contains mostly information on the situation prior to migration (including characteristics of grandparents) and on the situation of parents in France. The sample that surveys second generation, from now on referred to as *sample second*, contains mostly information on the situation of the children and on parental investments in their children.[5]

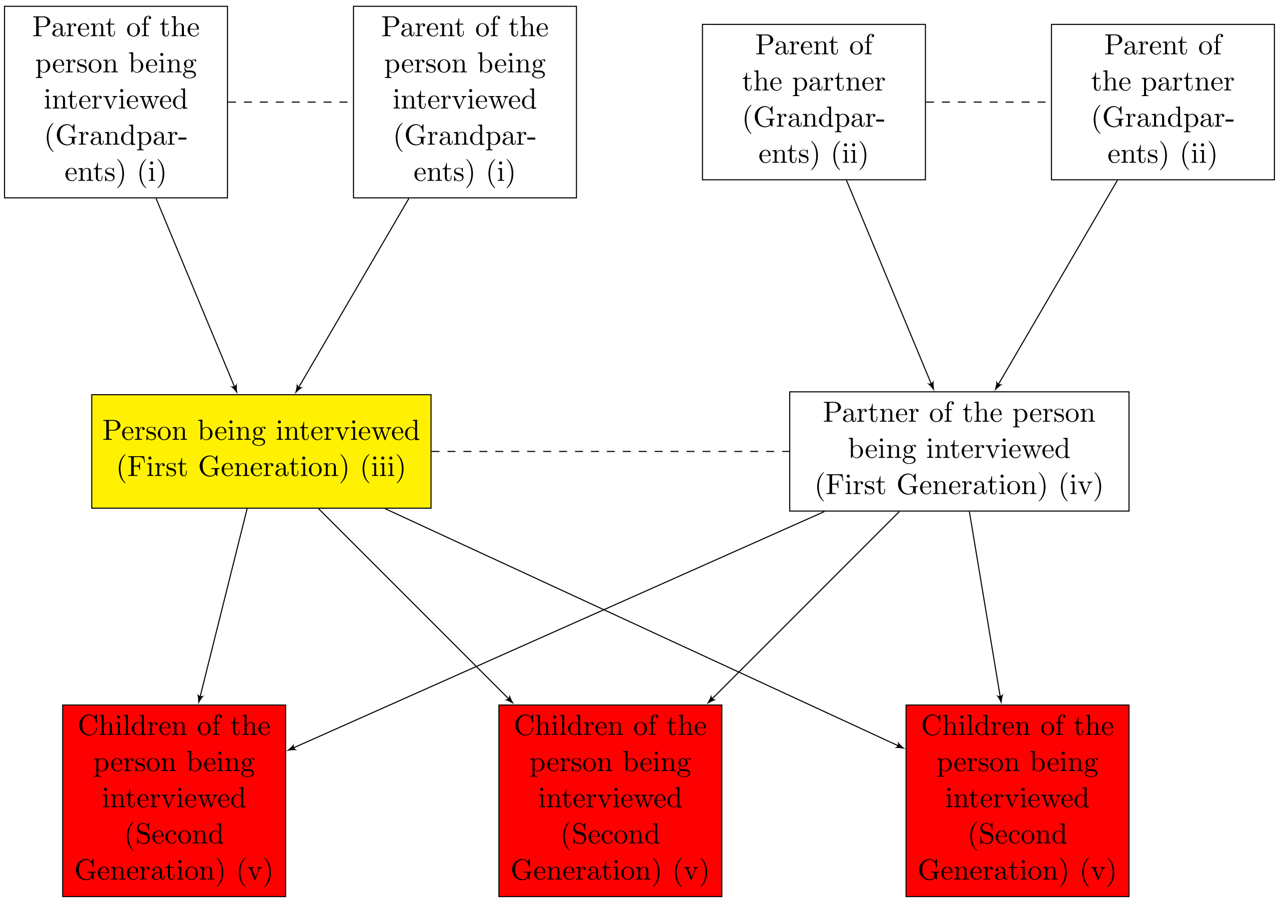
I use the following notation to refer to the situation of immigrants: $S_{j,t}$ describes

[5]Figures 1 and A1 show a digram (respectively for *sample first* and *sample second*) of who is being interviewed and how they relate to the population of interest. Recall that in *sample first*, parents are being interviewed, therefore information on several children in the same family is potentially available. Using *sample first* allows to stack three generations. This is why it is the main sample used in this paper, contrary to Ichou (2014) which relies uniquely on *sample second*.

the status of immigrants j in period t. Status refers to the information on education, occupation or household resources described below. The generations who grew up in the origin country are $j = P$ for parents (and grandparents), the generation who grew up in France is $j = C$ for children. There are three periods: $t = 0$ for pre-migration, $t = 1$ for the time of migration and $t = 2$ for present days.

The data is composed of immigrants who arrived in different years and at different ages. I perform robustness checks to confirm that the results are not driven by differences in migration periods. In everything that follows, second generation immigrants are people whose both parents are immigrants. They are referred to as the children, the population referred to as parents and grandparents are theirs.

Figure 1: Who is who? (*sample first*)



Note: The person being interviewed in TeO is in yellow, the population of interest in red.

2.2 Information on the situation in the origin country

In *sample first* I observe the level of education and occupation of parents and grandparents. I use these measures to classify $S_{P,0}$.[6] I use a categorical variable for occupation and calculate years of schooling from information on educational attainment.

The INSEE uses six categories to classify occupations: Self-Employed (S-E) Agriculture, S-E non Agriculture, High Managerial, Supervisory Occupation, Lower Services and Lower Technical. Immigrants tend to be over-represented among the lower socio-economic groups. Therefore, I use a variation of these six categories, in particular I group the "upper" categories together and break down the lower ones into finer groups: Managerial & S-E Non Agriculture, S-E Agriculture, Supervisory & Low Services, Low Technical, Lower Agriculture and Lowest Technical. This ensures a more uniform distribution among the groups.[7]

In *sample second* The only information available in this sample is the education of parents.

When using any of the samples, restrictions ensure that parents and grandparents acquired their HC in the origin country.[8] When I use several criteria together, I take the intersection of the different restrictions.

2.3 Information on the situation in the destination country

Information on parents' situation In *sample first*, the situation of parents is measured with the occupation in $t = 1$, just following migration and the occupation in $t = 2$

[6]Strictly speaking information on grandparents is measured at $t = 2$. However, education of the grandparents is more than likely to have been completed in the origin country (since grandparents did not migrate). Information about occupation is elicited though a general question about grandparents' occupation and not one that specifically refers to period $t = 2$

[7]Table A1 reports (i) the correspondence between default INSEE categories and the ones used in this paper and (ii) how years of education are imputed. Note that groupings are different for fathers and grandfathers since the raw distributions are different between the two. All the results are robust to reverting back to the usual categories.

[8]Restrictions are detailed in Tables A2 and A3.

at the time the survey was taken. It also contains additional information on career trajectories (a record of all employment and unemployment spells since arrival in France). In *sample second*, the situation of parents can be assessed by their occupation in $t = 2$.

Outcome variables for children In *sample first*, children's education level can be inferred through a question asked to their parents. They have to report if their children passed the baccalauréat, France's end of high school exam. $S_{C,2}$ is a binary variable taking value 1 if children passed the baccalauréat.

In *sample second*, more outcome variables are observed, in particular dropping out of school, obtaining the baccalauréat or obtaining a higher university degree. Sample restrictions ensures that children acquired their HC in France.[9]

Parental investment These are investments in developing the HC of their children. In *sample second*, children are asked whether in their youth, (i) they attended a different school than most children in their neighborhood, (ii) had additional private lessons, (iii) received help from their parents with their homework and (iv) had a room of their own to study.

2.4 Types of measurement errors and how to deal with them

Problems of measurement error are pervasive in the intergenerational mobility literature. I list the main ones and how this paper deals with them.

- The status of parents (and grandparents) is observed at specific points in time and may not be representative of life-long status (Black and Devereux, 2011). Many measures are stable through time (notably education of the parents and grandparents). When they are not (for instance parents' occupation just before and after migration), they are used because they correspond to crucial periods for the research question addressed in this paper. As a robustness check, I show that the

[9]For more details, see Tables A2 and A3 respectively for *sample first* and *second*.

results hold for immigrants who arrived relatively older (and for whom occupation before migration may be a more relevant indicator of HC level).

- Recollection errors. To minimize them, I use answers to questions concerning the preceding or following generation (parents about grandparents, children about parents, etc.). When possible, I rely on several measures.

- Misclassification errors that could arise because of modifying the usual INSEE categories. I provide robustness checks using the usual categories.

All results are robust to using different measures of family status (occupation, education of the parents/grandparents), which alleviates concerns about measurement error.

2.5 Descriptive Statistics

Table 1 provides basic descriptive statistics on first generation immigrants in *sample first* by gender. I report the distribution of educational level and that of the father (the grandfather from the perspective of second generation immigrants), birth year, year in which they migrated and occupation before migrating.[10]

There is variation in the pre-migration characteristics. The education level of first-generation immigrants roughly splits in three groups of equal size: below primary school, primary school and above primary. The origin of immigrants is also widespread with 36% coming from Europe, 23% from North-Africa and 13% from Sub-Saharan Africa. Most of them arrived in the 1970s and early 1980s.

3 Resurgence of pre-migration characteristics

3.1 Estimated Equation

Equation 1 tests if pre-migration background $S_{P,0}$ has an effect on the educational outcomes of children. Table 2 reports the OLS estimation of the following regression:

[10] In table A4, a similar table is produced for the parents of immigrants followed in *sample second* (with the information available for that sample).

Table 1: Descriptive Statistics

	Men		Women	
	Numbers	%	Numbers	%
	Education Level			
< Primary School	402	30.07	563	35.12
Primary School	517	38.67	616	38.43
Secondary Education	161	12.04	180	11.23
Higher Education	257	19.22	244	15.22
	Pre-Migration Occupation			
Managerial & S-E Non Agriculture	110	17.92	105	19.27
Supervisory & Low Services	140	22.80	284	52.11
S-E Agriculture	61	9.93	36	6.61
Low Technical	143	23.29	29	5.32
Lowest Technical	116	18.89	68	12.48
Low Agriculture	44	7.17	23	4.22
	Education Level Grandfather			
< Primary School	877	68.30	1,053	64.05
Primary School	257	20.02	342	20.80
Secondary Education	56	4.36	93	5.66
Higher Education	94	7.32	156	9.49
	Occupation Grandfather			
Managerial & Supervisory	152	11.40	256	14.89
S-E Non Agriculture	201	15.08	277	16.11
S-E Agriculture	218	16.35	230	13.38
Low Services	119	8.93	158	9.19
Low Technical	354	26.56	426	24.78
Lowest Technical	195	14.63	259	15.07
Low Agriculture	94	7.05	113	6.57
	Origin			
Europe	500	36.26	648	36.08
Sub-Saharan Asia	318	23.06	350	19.49
Africa	181	13.13	264	14.70
North-Africa	322	23.35	456	25.39
Other	58	4.21	78	4.34
	Distribution of years			
	Year of birth			
25th Percentile	1952		1954	
Median	1956		1958	
75th Percentile	1961		1964	
	Year of arrival			
25th Percentile	1970		1972	
Median	1975		1979	
75th Percentile	1982		1986	

Note : The observations are parents of second generation immigrants followed in *sample first*. I report the gender of the parent being interviewed, year of birth, year of migration, education level and occupation before migration. I also report the occupation and education level of their father, i.e. the grandfather of second generation immigrants. For instance, the entry 877 should be read as follows; among first generation male immigrants, 877 had a father who completed less than primary school.

$$(S_{C,2})_i = \alpha + \beta_1 (S_{P,0})_i + \gamma' X_i + \varepsilon_i \tag{1}$$

Subscript i refers to children and X is a vector of controls. Column 1 does not include controls. The second column adds information on the occupation of the father in France ($S_{P,2}$) and gives the baseline results. Note that this specification looks at the effect of pre-migration background above and beyond father's occupation in the destination country. It resembles an AR(2) model. Column 3 adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects while column 4 adds family controls (number of siblings, birth order and number of years since the father arrived in France).

Origin country characteristics are measured as father's pre-migration occupation in panel A and grandfather's occupation in panel B.[11] For both panels, the category "Lowest Technical" is taken as the reference. Results should be read as follows, for a given father's occupation in France, children of a former "Low Services" (for instance) have β_1 percentage point more/less changes of obtaining the baccalauréat than someone whose father was a "Lowest Technical". In addition to showing individual coefficients for $S_{P,0}$, I report the F-tests of $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (F-test Post-Migration). Standard errors are clustered at the family level, as in Catron (2020).

3.2 Results

Pre-migration characteristics have a strong influence on the educational attainment of the second generation (beyond current occupation of the father). Conditional on the current social situation in the destination country, having a father who had a "Managerial & S-E Non-Agriculture" position pre-migration is associated with a 16-18 percentage points increase in the probability of obtaining the baccalauréat. This corresponds to a 28-31% increase from the unconditional probability (58%). Effects are even larger when looking at

[11]To avoid issues related to female labor force participation, Panel A only includes fathers. To be consistent, Panel B only includes grandfathers from the father's side. Results including both grandfathers are similar and available upon request.

Table 2: Importance of Pre-Migration Background

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.21***	0.16***	0.18***	0.17***
	(0.056)	(0.059)	(0.064)	(0.065)
Supervisory & Low Services	0.08	0.06	0.07	0.06
	(0.058)	(0.057)	(0.061)	(0.062)
S-E Agriculture	-0.03	-0.07	-0.06	-0.03
	(0.070)	(0.071)	(0.069)	(0.071)
Low Technical	-0.01	-0.04	-0.04	-0.05
	(0.058)	(0.059)	(0.061)	(0.059)
Low Agriculture	-0.06	-0.03	-0.04	-0.02
	(0.076)	(0.081)	(0.084)	(0.080)
Mean Outcome	0.58	0.58	0.58	0.58
R-Squared	0.028	0.048	0.082	0.107
Nb of Observations	1175	1146	1146	1146
F-test Pre-Migration	5.75	3.71	4.44	3.43
F-test Post-Migration		2.29	1.31	1.61
Panel B: Grandfather Occupation				
Managerial & Supervisory	0.31***	0.26***	0.26***	0.25***
	(0.063)	(0.066)	(0.064)	(0.065)
S-E Non Agriculture	0.23***	0.18***	0.16**	0.16**
	(0.063)	(0.065)	(0.066)	(0.064)
S-E Agriculture	0.03	0.03	0.02	0.03
	(0.061)	(0.062)	(0.061)	(0.059)
Low Services	0.14*	0.12	0.11	0.11
	(0.074)	(0.075)	(0.074)	(0.070)
Low Technical	0.03	-0.00	-0.01	-0.01
	(0.069)	(0.072)	(0.069)	(0.066)
Low Agriculture	0.03	0.08	0.06	0.07
	(0.074)	(0.073)	(0.072)	(0.073)
Mean Outcome	0.58	0.59	0.59	0.58
R-Squared	0.045	0.062	0.095	0.122
Nb of Observations	1560	1516	1516	1515
F-test Pre-Migration	10.25	6.44	6.75	5.40
F-test Post-Migration		3.82	2.75	2.54
Occupation Father ($S_{P,2}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Origin FE	NO	NO	YES	YES
Family Controls	NO	NO	NO	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (from the father's side) occupation. The second column controls for father's occupation in France. The third column adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects. The last column adds family controls (number of siblings, birth order and number of years since the father arrived in France). Each panel reports the F-test for $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (F-test Post-Migration). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B) grandfather's occupation. Results are concentrated at the top, pre-migration advantage is strongly transmitted.

The magnitude of the effects can also be assessed by comparing the F-test for the nulls $\mathbb{H}_0 : S_{P,0} = 0$ and $\mathbb{H}_0 : S_{P,2} = 0$. For both panel A and B, the value of the test is larger for pre-migration characteristics than for post. In particular in columns 3 and 4 of panel A, the null $\mathbb{H}_0 : S_{P,2} = 0$ cannot be rejected at conventional level while the null $\mathbb{H}_0 : S_{P,0} = 0$ can. Controlling for pre-migration background, post-migration characteristics lose their (joint) statistical significance; but not the other way around.

Results are robust to adding powerful controls. Coefficient values are stable to including $S_{P,2}$. They are almost unchanged, remain large and highly significant when accounting for many individual and family controls. The strong effect of pre-migration characteristics is the main result of this paper.

3.3 Robustness Checks

Specification Table A5 reports estimates of a probit model. Table A6 reports weighted OLS regressions.[12] They confirm the results from Table 2.

Measurement Results are robust to a variety of measurement error. Occupation of parents and grandparents could be poorly captured by the re-bundling of occupation categories. Table A7 uses the usual INSEE categories.

Following Solon (1992), Figure A2 uses an average of two measures ($S_{P,0}$ and $S_{P,1}$) to categorize parents' pre-migration characteristics. Although $S_{P,1}$ is not measured in the origin country, it corresponds to the first observation after arrival and could arguably be indicative of some pre-migration characteristics. Since it is not possible to take an average of categorical values, I simulate 250 samples in which I categorize fathers by $S_{P,1}$ with probability a half and by $S_{P,0}$ in the remaining cases. I estimate equation 1 for each simulated sample (specifically the specification of column 4 in Table 2). I plot the mean of the results in Figure A2. They are very close to the main estimates.

[12] Using frequency weights provided by TeO.

If fathers immigrated very young, their occupation pre-migration could poorly represent their lifetime potential in the origin country. When restricting the sample to people who migrated at 24 y.o. or older (threshold used to observe outcomes at adulthood in Chetty and Hendren (2018)), the picture remains the same (although sample size is greatly reduced, see Table A8). Results are also robust to focusing on immigrants who were childless when they migrated (see Table A9). The relevant family background to assess status in France (to use as a control) could be $S_{P,1}$ and not $S_{P,2}$. In Table A10, I reproduce Table 2 with this alternative measure.

Using sample second The results are confirmed when using *sample second*. Table A11 shows a strong positive effect of parents' education (conditional on father's occupation) not only on the probability of obtaining the baccalauréat but also on the probability of not dropping out and having a higher education degree.

3.4 Heterogeneous Effects

How important is pre-migration background in understanding upward mobility? Is the advantage of having a father (or a grandfather) who had a managerial position concentrated among immigrants who remained (or became) managers after migration? Or is it similar for those with a low-skilled technical position? This dimension of heterogeneity is important since the public debate focuses on the success of second generation immigrants coming from a low SES background.

Because of sample size issues, it is not possible to interact pre and post migration characteristics. Instead, I reproduce the estimation of equation 1 and remove successively $S_{P,2}$ categories from the highest to the lowest. If the coefficients vary substantially when removing occupational categories observed in France, this would mean that the effect is heterogeneous. Since $S_{P,2}$ categories are sequentially removed from Table 3 and, sample size diminishes as categories are dropped, I do not include $S_{P,2}$ as a regressor and use the specification corresponding to column 1 of Table 2.

The positive effect associated with a high pre-migration background is relatively ho-

Table 3: Importance of Pre-Migration Background - Heterogeneity

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.20***	0.17**	0.17**	0.18
	(0.067)	(0.079)	(0.079)	(0.108)
Supervisory & Low Services	0.04	-0.01	-0.01	-0.17
	(0.063)	(0.077)	(0.077)	(0.106)
S-E Agriculture	-0.05	-0.02	0.00	0.08
	(0.073)	(0.079)	(0.079)	(0.114)
Low Technical	-0.03	-0.01	-0.02	0.01
	(0.062)	(0.071)	(0.071)	(0.131)
Low Agriculture	-0.10	-0.09	-0.09	-0.15
	(0.077)	(0.080)	(0.083)	(0.125)
Mean Outcome	0.55	0.52	0.52	0.47
R-Squared	0.022	0.013	0.013	0.044
Nb of Observations	982	767	753	297
Panel B: Grandfather (of the father) Occupation				
Managerial & Supervisory	0.32***	0.30***	0.30***	0.39***
	(0.071)	(0.091)	(0.091)	(0.128)
S-E Non Agriculture	0.26***	0.24***	0.24***	0.39***
	(0.071)	(0.081)	(0.081)	(0.126)
S-E Agriculture	0.05	0.05	0.06	0.12
	(0.065)	(0.072)	(0.072)	(0.102)
Low Services	0.12	0.11	0.11	0.16
	(0.082)	(0.094)	(0.094)	(0.118)
Low Technical	0.12	0.09	0.09	0.04
	(0.074)	(0.089)	(0.089)	(0.132)
Low Agriculture	0.02	0.02	0.02	0.08
	(0.078)	(0.082)	(0.082)	(0.123)
Mean Outcome	0.56	0.52	0.52	0.50
R-Squared	0.044	0.032	0.031	0.065
Nb of Observations	1253	945	928	375
Managerial & S-E Non Agriculture	NO	NO	NO	NO
Supervisory & Low Services	YES	NO	NO	NO
S-E Agriculture	YES	YES	NO	NO
Low Technical	YES	YES	YES	NO
Lowest Technical	YES	YES	YES	YES
Low Agriculture	YES	YES	YES	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (of the father) occupation. The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B). Each column excludes observations based on father's occupation in France $S_{P,2}$. Column 1 to 4 successively drops immigrants whose father is "Managerial & S-E Non Agriculture", "Supervisory & Low Services", "S-E Agriculture" and "Low Technical".

mogeneous. The coefficients of "Managerial & S-E Non-Agriculture" categories are stable in both panel A (father's pre-migration occupation) and B (grandfather occupation).[13] Coefficients become imprecise as categories are dropped and the sample becomes (much) smaller. This is particularly true for column 4. However, the general picture from Table 2 does not change when the emphasis is put on low categories.

These results point to the difficulty of interpreting trends in intergenerational mobility when the environment is not in steady state (Nybom and Stuhler, 2014). For many immigrants the information pre and post migration is not redundant and the success of many low SES (in the destination country) second generation can be traced back to their pre-migration advantage. This puts cautious on over-interpreting the mobility observed when only using destination country characteristics.

Robustness Checks Results are robust to using a probit specification (Table A12), sample weights (Table A13) and usual INSEE categories for occupations (Table A14).

4 Comparing natives and immigrants

Although pre-migration status is specific to immigrants (Panel A of Table 2), grandparent characteristics can also affect the educational achievements of natives. The literature on social mobility which combines information over three generations has shown that a "grandparent effect" is not specific to immigrants (Mare, 2011; Chan and Bolivier, 2013; Olivetti and Paserman, 2015). In the case of immigrants, father's occupation in the destination country may not be a good indicator. Other (origin country) family characteristics should have more predictive power for that population. In this section, I show that the influence of grandparents' characteristics are more important for immigrants than for natives.

To do so, I follow two distinct but complementary approaches. The first one compares the predictive power of grandparents' characteristics for immigrants and natives. The

[13]For Panel B categories "Managerial & Supervisory" and "S-E Non-Agriculture".

second one compares the effect of increasing the educational level of grandparents for immigrants and natives. In the context of linear regressions, the first one focuses on the R^2, the second one on coefficient values. When comparing populations as different as natives and immigrants, the first option is my favorite one.[14]

4.1 Predictive power of grandparent characteristics

4.1.1 Using Machine Learning Techniques

I rely on random forest techniques.[15] Random forests are classification algorithms which construct a multitude of decision trees to predict an outcome. These techniques have the particularity of randomizing the variables which are used for splitting each tree. Since the algorithms change the variables used to train the forest, it can also be used to assess the relative importance of each variable.[16]

The criteria used to calculate variable importance is the change in mean decrease accuracy.[17] A large mean decrease accuracy indicates that a variable has an important predictive power. In the algorithm, the outcome variable is a dummy for having obtained the baccalauréat, explanatory variables include age, gender, characteristics of the parents and grandparents; namely parents' education in years, grandparents' education (of the parent being interviewed) in years and categorical variables for grandfathers' occupation

[14]The distribution of grandparents' education level differs greatly between immigrants and natives. For instance, 30% of native grandmothers and 22% of native grandfathers have not completed primary school, when these numbers are above 64% (see Table 1) for immigrants. This means that comparing the effect (between immigrants and natives) of a marginal increase in years of schooling corresponds to looking at changes from two very distinct points of the unconditional distribution.

[15]For an introduction, see (Breiman, 2001; Biau and Scornet, 2016). Random forests are very popular in Machine Learning because of the easiness of their implementation and the robustness of their results.

[16]While Blundell and Risa (2019) also use Machine Learning techniques to compare different models of intergenerational mobility, their approach is centered on the notion of completeness (Fudenberg et al., 2019). They focus on what share of "explainable" variation can a particular model of intergenerational mobility account for. I depart from that approach in that I do not use Machine Learning techniques to discriminate between models.

[17]The algorithm builds a forest from many decision trees. Each tree is based on a bootstrapped sample. For each tree, the observations which are not used in the bootstrap are called the out of bag (OOB) sample. Once a decision tree is built, the OOB are passed through the tree. To assess the importance of variable j, the algorithm permutes the value of OOB observations (i.e. change the value for one observation by that of another one from OOB and calculate the decrease in accuracy). The decrease in mean accuracy of a variable is calculated by averaging the decerase over all trees. The distribution of decrease accuracy also allows to construct standard errors and confidence intervals (under normality).

and father's occupation (post-migration, i.e. $S_{P,2}$).[18] Figure 2 shows (in ascending order) which variables are highly predictive for both immigrants and natives.

Two elements stand out: (i) occupation of the father is (relative to other variables) less important for immigrants than natives and (ii) characteristics of grandparents are (relative to other variables) more important for immigrants. Occupation of the father has the second lowest decrease in accuracy for immigrants and is clearly ranked among the less informative variables of the model. On the contrary, father's occupation has a median variable importance for natives. Among four grandparent characteristics, two are significantly more predictive than father's occupation for immigrants (occupation of both grandfathers) while only one is for natives (the occupation of the grandfather on the mother's side). The education level of both grandparents is less predictive than father's occupation in the case of natives while only grandmother's education is less predictive for immigrants. This picture is confirmed in Figure A3 when I use the usual INSEE categories (rather the modified ones) for occupation of fathers and grandfathers.

4.1.2 Using R^2 as a measure of fit

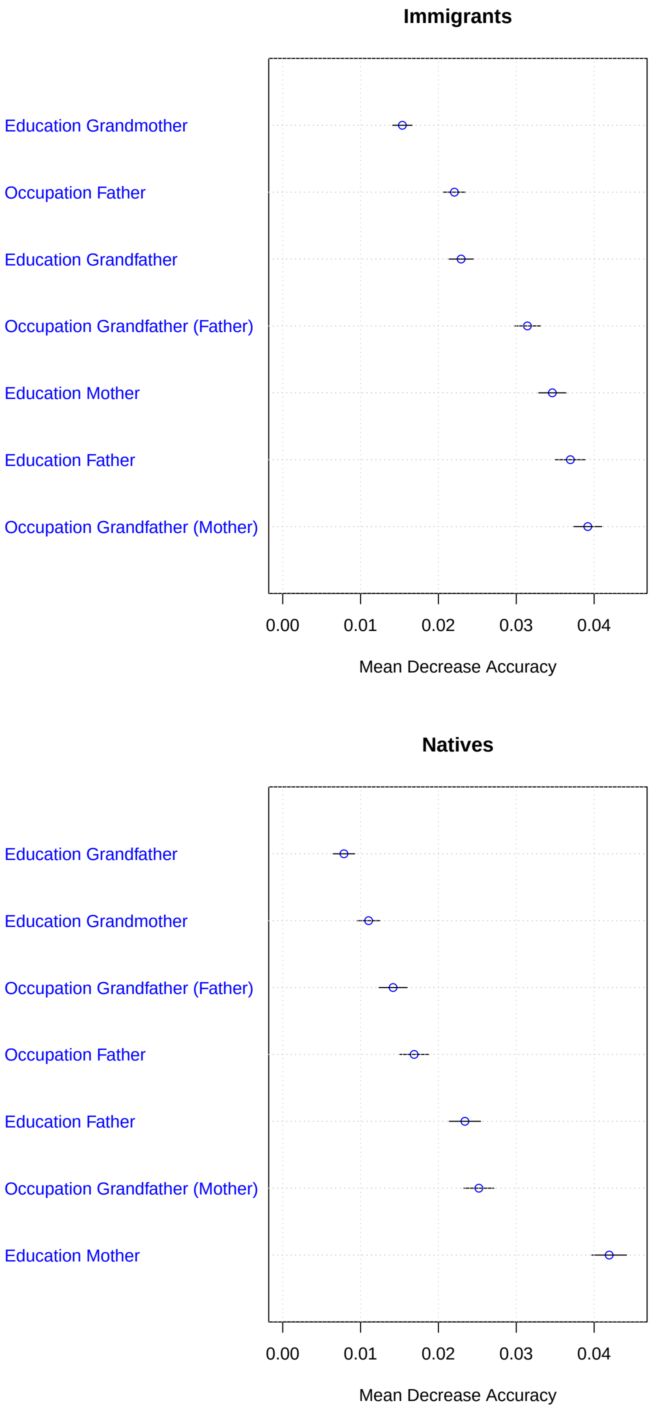
This section replicates the previous analysis using linear regressions. It focuses on the predictive power of parents' and grandparents' characteristics by analyzing how much of the variation in the outcome they can explain. I regress the main outcome, a dummy for having obtained the baccalauréat on age, gender and (separately) characteristic of the parents and grandparents (used in Figure 2). I use the adjusted R^2 as a measure of goodness of fit.

To provide confidence intervals, I rely on resampling techniques. I bootstrap each sample (natives and immigrants) 250 times and estimate a linear probability model on each of the iteration. Figure 3 shows the mean adjusted R^2 together with confidence intervals built from the distribution of estimates.

The two main elements highlighted in the previous section are confirmed when using

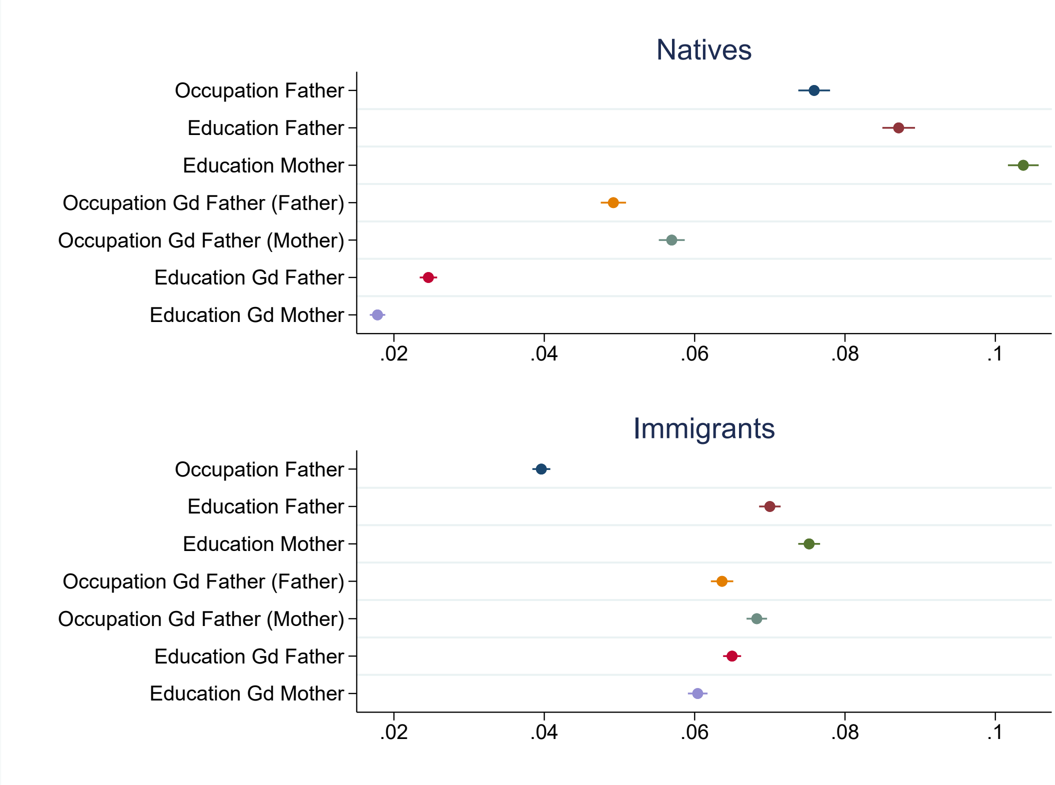
[18] Recall from Figure 1 and Table A2 that grandparent education is only observed for the parent being interviewed. I do not include pre-migration father's occupation since it is not applicable to natives.

Figure 2: Variable Importance (Random Forests) between Natives and Immigrants



Note: These Figures report variable importance calculation from random forests. The random forest algorithm includes the variables listed above, together with the gender and age (of the child). Random forests are run separately for immigrants and natives. Variable importance (and associated standard errors) are calculated from the mean decrease accuracy of the model across all trees. Confidence intervals are calculated assuming normality of the distribution of mean decrease accuracy among out of bag observations.

Figure 3: Comparing R^2 between Natives and Immigrants



Note: The Figures are based on 250 bootstrap samples from the populations of natives and immigrants. For each bootstrapped sample, I run a series of linear probability models where the outcome is having obtained the baccalauréat. The controls are age and gender and, the variable of interest is a characteristic of the parents or grandparents. The figure reports the average adjusted R^2 together with the confidence intervals (based on the standard errors from the distribution of adjusted R^2 in the bootstrapped samples).

linear regressions. The occupation of the father has a high R^2 (relatively) for natives but a small one (relatively) for immigrants. For the latter population, it is the characteristic that explain the smallest amount of variation in children's probability of obtaining the baccalauréat. On the other hand, characteristics of grandparents are (relatively) more informative for immigrants. They all have a similar R^2 which is itself close to the most predictive variables (parents' education). This situation contrasts with the results for natives where education of the grandparents have the lowest R^2 values.

Figures 2 and 3 are the results of very different estimation techniques. For instance linear regressions control for age and gender while random forests include them in the algorithm. However, they provide very consistent evidence; grandparent characteristics are more important in explaining the educational attainments of immigrants than natives. This picture is confirmed in Figure A4 when I use the usual INSEE categories rather the modified categories for occupation of parents and grandparents.

4.2 Looking at coefficients from linear regressions

To complement the previous analysis and use an approach more common in the literature (Lindahl et al., 2015; Braun and Stuhler, 2018; Adermon et al., 2021), I run linear regressions where I look at the effects of parents' and grandparents' education (separately and jointly) on the educational attainment of immigrants and natives.

Table 4 runs a linear probability model using education of the parents (in column 1), education of the grandparents (in column 2), information from all male relatives (father and grandfathers) or all female relatives in columns 3 and 4 and finally in column 5, jointly education of parents and grandparents. I also test the null hypothesis that all grandparent coefficients are zero.

When included alone (column 2), coefficients on grandparents' education are individually and jointly very significant. Including education of the parents mechanically decrease the magnitude of the grandparent effect. However it does it differently for immigrants and natives. While the effect virtually goes away for natives, it remains statistically significant for immigrants. For natives, the grandfather p-value remains significant at the 5% level (column 3), but the grandmother effect (column 4) does not. The last specification where background of the parents and grandparents are jointly included, has a very large p-value (0.994).[19] On the contrary, coefficients for grandparents remain significant (if not individually at least jointly) for immigrants even after including parents' education.

It is also interesting to compare the R^2 from column 2 and 5, for immigrants and natives. The last column includes the largest number of covariates and therefore achieve the highest R^2 of all models. Taking the ratio of the R^2 in columns 2 and 5 is indicative of how much information is carried by grandparent background as a fraction of all the variation that can be explained.[20] This ratio is much larger for immigrants than for natives (73% vs 26%) and is again indicative that the background of grandparents carry more information for immigrants than natives.

Robustness checks Results are robust to using a probit specification (see Table A15) and using weighted linear regressions (although grandparent coefficients in column 5 are only significant at the 10% level for immigrants, see Table A16).

5 Evidence on Mechanisms

This section looks at two mechanisms behind the resurgence of pre-migration social background: (i) the magnitude of skill downgrading and (ii) the effects of parental investments. The more downgrading there is, the less occupation in the destination country is informative about the level of immigrants' HC (Borjas, 2015; Abramitzky et al., 2021). Parents with higher pre-migration characteristics (but similar occupations in France) may also invest more in the development of their children's HC (Becker et al., 2020).

[19] The disappearance of the grandparent effect when including characteristics of the mother is also documented in Braun and Stuhler (2018).

[20] This calculation is related to the notion of "completeness" developed in Fudenberg et al. (2019).

Table 4: Grand-parents' education: Effect for immigrants and natives

	Immigrants					Natives				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Education Father	0.011***		0.012***		0.008***	0.019***		0.029***		0.019***
	(0.0024)		(0.0025)		(0.0027)	(0.0034)		(0.0033)		(0.0036)
Education Mother	0.012***			0.014***	0.010***	0.028***			0.035***	0.028***
	(0.0027)			(0.0027)	(0.0029)	(0.0038)			(0.0036)	(0.0039)
Gd Father - Mother		0.009**	0.009***		0.005		0.011*	0.006		0.001
		(0.0045)	(0.0031)		(0.0046)		(0.0057)	(0.0039)		(0.0051)
Gd Father - Father		0.013***	0.012***		0.006		0.003	0.010**		0.000
		(0.0043)	(0.0033)		(0.0046)		(0.0080)	(0.0039)		(0.0074)
Gd Mother - Mother		0.014**		0.013***	0.005		0.012*		0.007*	0.001
		(0.0053)		(0.0033)	(0.0053)		(0.0072)		(0.0042)	(0.0060)
Gd Mother - Father		0.011*		0.012***	0.005		0.022**		0.006	0.002
		(0.0060)		(0.0044)	(0.0059)		(0.0089)		(0.0044)	(0.0085)
Nb of Observations	2329	2329	2329	2329	2329	1329	1329	1329	1329	1329
R-Squared	0.073	0.057	0.067	0.067	0.078	0.154	0.040	0.103	0.129	0.154
F-test: Grandparent Effect		22.410	7.034	8.293	2.393		8.261	3.014	1.487	0.058
P-value		0.000	0.001	0.000	0.049		0.000	0.050	0.227	0.994

Note: This Table reports estimates from linear probability models where the outcome is having obtained the baccalauréat. All regressions control for age and gender of the young adult (child of immigrants and natives). The first five columns report results on immigrants, the five last on natives. All covariates of interest refer to years of education (of parents or grandparents). Grandparents' education is interacted with the gender of the parent being interviewed to allow for the effect to differ between grandparents from the mother's or father's side. The table reports the F-test (and associated p-values) of the null: all grandparents coefficients in the column are zero. Standard errors are clustered at the family level.

5.1 Evidence on skill downgrading

Table 5 is a transition matrix between occupations in the origin and destination countries. It reports conditional probabilities; the last column and last row reporting raw numbers. To assess downgrading, one should focus on the probability to move to the same or to a lower occupation when migrating. This is captured by the upper triangular part of the matrix. There is clear evidence that a large share of immigrants who had a high type occupation loses their advantage in the labor market upon arrival. For instance, almost two thirds (63.6%) of the immigrants who held a “Managerial & S-E Non Agriculture” position are not able to find a similar job when arriving in France. Almost half of them (48.6%) end up in a technical occupation (“Low Technical”, “Lowest Technical” and “Low Agriculture”), which is clear evidence of skill downgrading. Similarly, almost half (48.5%) of immigrants who previously worked as “Supervisory & Low Services” category end up in a technical occupation.

When focusing on immigrants with a technical occupation before migration (“Low Technical”, “Lowest Technical” and “Low Agriculture”), the magnitude of the change mechanically decreases. Their chances of starting their career in another category than a lower technical occupation (“Managerial & S-E Non Agriculture” or “Supervisory & Low Services”) is very small (15.4% for the initially “Low Technical”, 10.8% for the “Lowest Technical” and 4.6% for “Low Agriculture”). Table A17 shows that the picture is unchanged when focusing on immigrants arriving relatively old (after 24 years old). Table A18 addresses potential concerns arising from immigrants arriving from different countries and at different periods.[21]

Evidence on employment trajectories I test whether the difference between status before migration and later in France is due to this initial downgrading and not to

[21] To see if the results vary by origin countries or year of arrival, I run the following regression (reported in table A18) where the dependent variable is a dummy for “high” occupation in $t = 1$ (Managerial, S-E Non-Agriculture and Supervisory) and the main regressor a categorical variable for $S_{P,0}$. I run the regressions without controls in the first column and add successively year of birth fixed effects, year of arrival fixed effects, age at arrival and origin fixed effects. If the coefficients of interest vary a lot with the inclusion of extra regressors, this is indicative that the result is driven by the conditions at the time of arrival. The coefficients are insensitive to adding controls.

Table 5: Skill downgrading among first generation immigrants

Occ. before Migration	Occupation at Arrival: Managerial & S-E Non Agriculture	Supervisory & Low Services	Low Technical	Lowest Technical	Low Agriculture	Total
Managerial & S-E Non Agriculture	36.4	15.0	31.8	14.0	2.8	107
	(4.66)	(3.45)	(4.50)	(3.36)	(1.60)	
Supervisory & Low Services	8.0	43.5	18.8	26.8	2.9	138
	(2.31)	(4.22)	(3.33)	(3.77)	(1.43)	
S-E Agriculture	0.0	7.0	28.1	42.1	22.8	57
	(0.00)	(3.39)	(5.96)	(6.55)	(5.56)	
Low Technical	0.7	14.7	58.7	23.1	2.8	143
	(0.70)	(2.96)	(4.12)	(3.53)	(1.38)	
Lowest Technical	0.9	9.6	18.3	63.5	7.8	115
	(0.87)	(2.74)	(3.61)	(4.49)	(2.51)	
Low Agriculture	2.3	2.3	34.1	29.5	31.8	44
	(2.25)	(2.25)	(7.15)	(6.88)	(7.03)	
Total	53	113	196	195	47	

Note: This Table reports the transition between occupation before migration in the origin country (rows) and first occupation in France (columns). The Table reports conditional probabilities; the last row and the last column report raw numbers. The observations are fathers of (adult) second generation immigrants followed in sample first. Numbers in parenthesis are standard deviation.

subsequent differences in career trajectories. To do so, Table 6 looks if pre-migration background is related to the probability of being unemployed at arrival and/or of going through fewer/more employment and unemployment spells over one's career. The first column reports OLS estimates from a linear probability model where the outcome is a binary variable for reporting unemployment as the first professional experience. The second and third columns report OLS results of the number of employment and unemployment spells once in France. These outcomes are indicative on the process of HC accumulation in the destination country.[22] All regressions control for origin fixed effects and individual controls (age and age squared).

Table 6: Unemployment at and after arrival

	Unemployment at arrival	Nb of unemployment spells	Nb of employment spells
Managerial & S-E Non Agriculture	-0.015	-0.063	-0.131
	(0.0360)	(0.1001)	(0.1276)
Supervisory & Low Services	0.013	-0.084	0.100
	(0.0367)	(0.0894)	(0.1378)
S-E Agriculture	0.061	-0.042	-0.158
	(0.0485)	(0.1115)	(0.1526)
Low Technical	-0.028	-0.074	-0.092
	(0.0274)	(0.0837)	(0.1072)
Low Agriculture	0.031	-0.064	-0.132
	(0.0482)	(0.1317)	(0.1466)
Individual Controls	YES	YES	YES
Origin FE	YES	YES	YES
R-Squared	0.03	0.03	0.02
Nb of Observations	604	604	604
Mean Outcome	0.07	0.36	1.46
P-value	0.34	0.96	0.41

Note: This Table reports linear regressions of a dummy variable for being unemployed at the time of arrival (column 1), the number of unemployment and employment spells (column 2 and 3) since arrival in France. The baseline category is having worked as a "Lowest Technical" before migration. Regressions include origin fixed effects and individual controls (age and age square). Each column reports the p-value associated with the null hypothesis that all pre-migration categories are zero. Standard errors are robust to heteroskedasticity. The observations are fathers of (adult) second generation immigrants.

The baseline category is being a "Lowest Technical" before migration. In addition to

[22] These results are robust to using Poisson regressions rather than OLS. They can be provided upon request.

single coefficients, Table 6 reports the p-value of the joint hypothesis that all pre-migration categories are the same. There is no evidence of a difference in the probability of first being unemployed: no coefficient is statistically significant and the p-value of the joint test is larger than 0.3.[23] There is no evidence of a difference in the number of employment and unemployment spells. This is indicative evidence that the difference between pre-migration categories is driven by the initial downgrading at arrival.

5.2 Evidence on parental investments

How much does parental investment relate to pre-migration characteristics? I first show that immigrants with a higher socio-economic background provide higher levels of parental investment. I then provide evidence that these investments pay off. The two results put together are indicative that parental transmission is playing a role in the resurgence of family background. Recall that information about parental investment come from *sample second*.

5.2.1 Investment levels

As pointed out in Becker et al. (2020), immigrants put more emphasis on the transmission of HC since it is the only form of capital that they can always carry with them. In the setting of this paper, this implies that pre-migration characteristics determine investment levels above and beyond parents' characteristics in the destination country.

Table 7 documents this pattern. I regress four types of parental investment (sending children to a school outside the neighborhood "Strategy", helping with homework "Help Homework", providing a room where children can study alone "Room to study" and paying for private classes "Private Classes") on pre-migration characteristics controlling for occupation of the father in France, age, gender (of the child and of the parent being inter-

[23] There could be a measurement issue if people who were out of a job for a long time after they arrived do no report unemployment as their first experience but rather the first job they had (some time after arrival). To account for this problem, I perform the following robustness check: I recode as starting unemployed everyone whose first occupation was not reported the same as the year they reported arriving in France. Results are similar to Table 6 and available upon request.

viewed), number of siblings and origin fixed effects.[24] In addition to individual coefficients, I report the F-test and associated p-value of the hypothesis that the education of both parents have a null effect. There is clear evidence that pre-migration characteristics play a role; the coefficients are positive and jointly significant for three out of four types of investment.

Table 7: Parental Investments - Differences in levels

	Strategy	Help Homework	Room to study	Private classes
Education Father	0.002	0.008**	0.004	0.005*
	(0.0030)	(0.0033)	(0.0041)	(0.0026)
Education Mother	0.002	0.030***	0.007	0.007**
	(0.0032)	(0.0035)	(0.0044)	(0.0028)
Individual Controls	YES	YES	YES	YES
Origin FE	YES	YES	YES	YES
F-test	1.23	76.10	3.70	11.52
P-value	0.29	0.00	0.03	0.00
Mean Outcome	0.14	0.24	0.61	0.11
R-Squared	0.02	0.21	0.04	0.06
Nb of Observations	1123	1113	1136	1136

Note: This Table reports the results of a regression of parental investments (the four columns, sending children to a school outside the neighborhood "Strategy", helping with homework "Help Homework", providing a room where children can study alone "Room to study" and paying for private classes "Private Classes") on pre-migartion family status proxied by parents' education. Controls include age, gender (of the child and of the parent being interviewed), number of siblings, occupation of the father in France and origin fixed effects. I also report the mean outcome value together with the p-value associated with the F-test both parent education coefficient is null.

5.2.2 Returns on investment

For each potential outcome used in *sample second* (Baccalauréat, Not Dropping Out and Higher Education) and every measure of investment available, I regress the outcome on the type of investment interacted with a dummy for immigrants and natives (and a series of individual controls; namely age, gender, number of siblings, occupation of the father and origin fixed effects). This gives the following equation to estimate:

$$y_i = \alpha + \sum_{j=0}^{1} \sum_{l=0}^{1} \beta_{j,l} 1 \left\{ \text{Native}_i = j, \text{Investment}_i = l \right\} + \gamma X_i + \varepsilon_i \tag{2}$$

[24]Recall from Figure A1 and Table A3 that pre-migration background in *sample second* is measured with education of the parents.

This allows to test whether the returns to investment are positive but also if they are lower, larger or similar for immigrants and natives. Results are reported in Table 8.[25] Returns to parental investment for immigrants are particularly high. They are either indistinguishable or if anything higher than for natives. The last row of the panel reports the p-value of the F-test associated with the null of equality between the two coefficients. It fails to reject the null (at the 5% level).

Table 8: Parental Investments - Comparing returns between Immigrants and Natives

	Strategy	Help Homework	Room to study	Private classes
Immigrants	0.16***	0.14***	0.02	0.17***
	(0.038)	(0.033)	(0.029)	(0.042)
Natives	0.09*	0.06*	0.06*	0.15***
	(0.051)	(0.038)	(0.038)	(0.050)
Individual Controls	YES	YES	YES	YES
Origin FE	YES	YES	YES	YES
Mean Outcome	0.52	0.53	0.52	0.52
R-Squared	0.09	0.09	0.09	0.09
Nb of Observations	1607	1659	1688	1688
P-value	0.28	0.07	0.17	0.66

Note: This Table presents the results of estimating equation 2 where the outcome is obtaining the baccalauréat. Estimation is performed on a sample of second generation immigrants and natives. The rows referred to as Immigrant and Natives are the coefficients associated with investing and being an immigrant or a native. Controls include age, gender (of the child and of the parent being interviewed), number of siblings, occupation of the father in France and origin fixed effects. Each column reports the p-value associated with the hypothesis of equality between the two coefficients reported.

6 Conclusion

In this paper, I look at the long-term assimilation of immigrants and see how it is influenced by the socio-economic status pre-migration/in the home country. Using unique French survey data, I reconstitute family histories over three generations, partially in the origin country, partially in France. I find evidence of a U-shape pattern; immigrants were heterogeneous before migrating, this heterogeneity is greatly reduced with the first generation and reappears with the second generation. I quantify the determinants of immigrants'

[25] Results with alternative outcomes (Not Dropping Out and Having a Higher Education degree) can be found in Table A19

and natives' intergenerational mobility and show that immigrants are more sensitive to the background of their grandparents than are natives. These facts are consistent with mechanisms suggesting that parents cannot fully transfer their human capital between labor markets but transmit it across generations.

There are two main takeaways from this paper which are interesting to the general discussion on the success of second generation immigrants. First, when assessing the achievements of second generation immigrants, it is critical to remember that the relevant starting point for this population may not be the situation in the destination country. Social mobility is indeed lower for immigrants when one takes a long-term perspective. The second takeaway is that there is a dichotomy between what happens in the labor market and what happens in the household following migration. Immigrants may be downgraded in the labor market, but they still are able to transmit the benefits of their previous socioeconomic status to their children.

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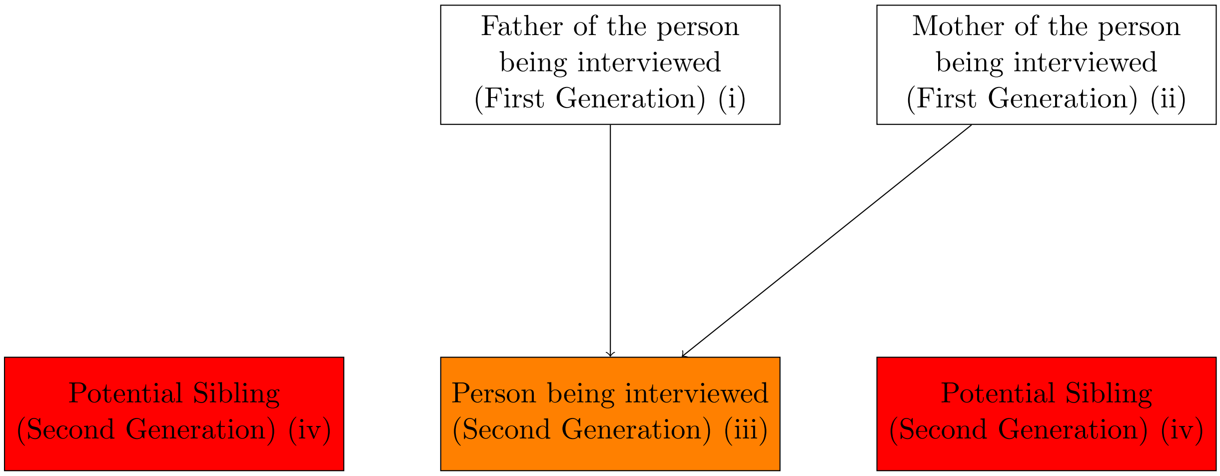
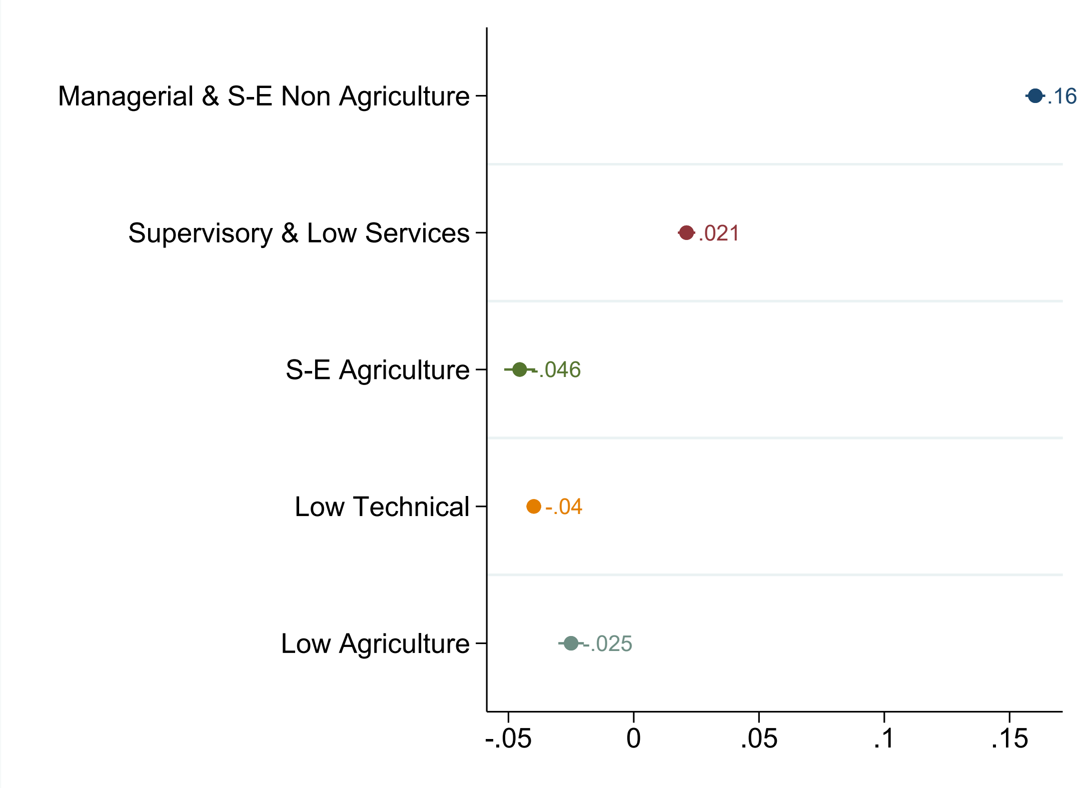
Appendix - For online publication only

Figure A1: Who is who? (*sample second*)



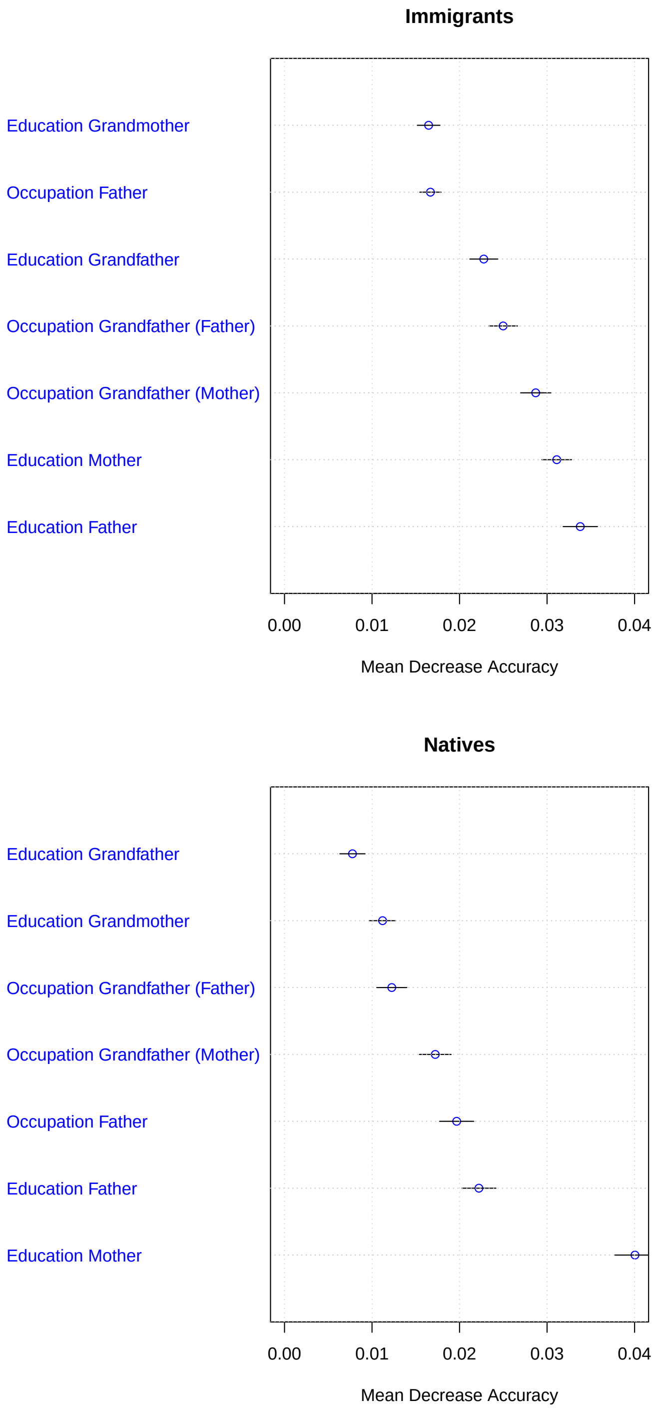
Note: Consider that the person being interviewed in TeO should be in yellow and that the population of interest in red. Since the person interviewed is also from the population of interest, it is orange.

Figure A2: Importance of Pre-Migration Background: Robustness to Measurement Error



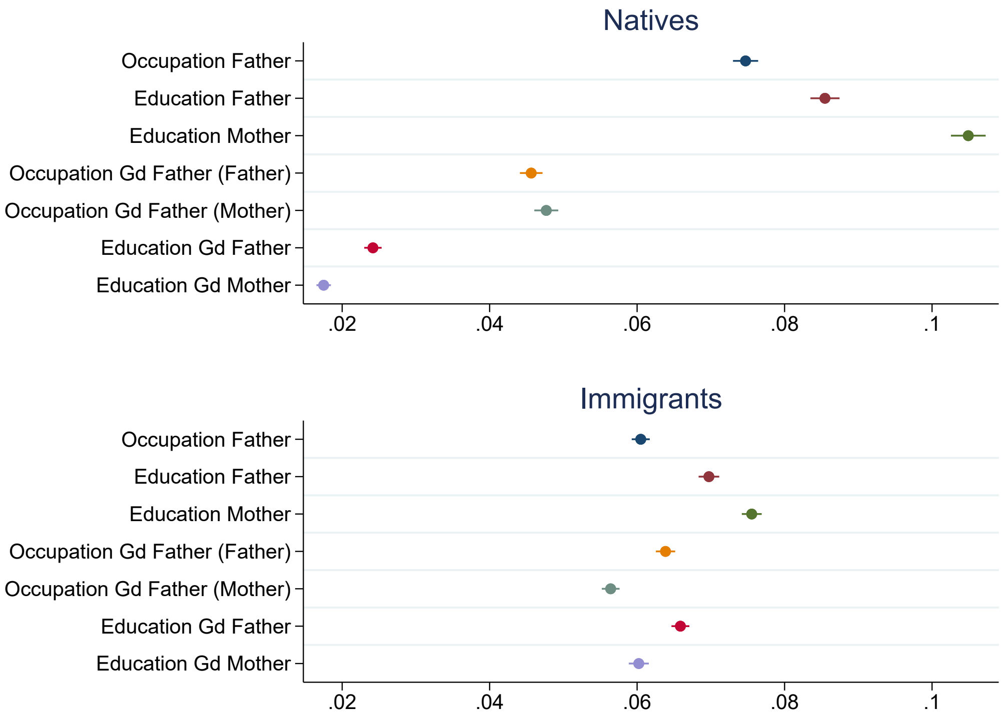
Note This graph is based on 250 simulations. It reproduces results similar to panel A of Table 2. In each simulation, pre-migration status is defined as first occupation in France, $S_{P,1}$ (with probability 0.5) or as pre-migration occupation $S_{P,0}$ (in the remaining cases). I estimate a linear probability model on each simulated sample and present the mean coefficient (with confidence intervals based on the standard errors from the distribution of estimates). Control variables in the regressions include father's occupation in France, individual controls (age and gender of the child, age of the father at the time of the interview), origin fixed effects and family controls (number of siblings, birth order and number of years since the father arrived in France). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration.

Figure A3: Variable Importance (Random Forests) - Usual INSEE Categories



Note: These Figures report variable importance calculation from random forests. The random forest algorithm includes the variables listed above, together with the gender and age (of the child). Random forests are run separately for immigrants and natives. Variable importance (and associated standard errors) are calculated from the mean decrease accuracy of the model across all trees. Confidence intervals are calculated assuming normality of the distribution of mean decrease accuracy among out of bag observations.

Figure A4: Comparing R^2 between Natives and Immigrants - Usual INSEE Categories



Note: The Figures are based on 250 bootstrap samples from the populations of natives and immigrants. For each bootstrapped sample, I run a series of linear probability models where the outcome is having obtained the baccalauréat. The controls are age and gender and, the variable of interest is a characteristics of the parents or grandparents. The figure reports the average adjusted R^2 together with the confidence intervals (based of the standard errors from the distribution of adjusted R^2 in the bootstrapped samples).

Table A1: Coding of Occupation and Education

Education

Category	Nb of years
No degree at all, no reported schooling (but not missing variable)	0
Some primary school	2.5
Finished Primary School	5
Some Junior High School	7.5
Finished Junior High School	9
Junior High School + 2 (“CAP & BEP”)	11
Finished High School or reported some above Junior High	12
Some College	14
3 year College degree (“Licence”)	16
Master degree (or equivalent)	17
PhD	20

Usual INSEE	Modified Categories	Splitting criteria (CS42 Nomenclature)
Occupation Father		
S-E Agriculture	S-E Agriculture	
S-E non Agriculture High Managerial	High Managerial & S-E Non Agriculture	
Supervisory Occ. Lower Services	Supervisory Occ. & Lower Services	
Lower Technical	Low Technical	All “Lower Technical” cat. but 67-68-69
	Lowest Technical	Unskilled Worker (cat. 67 & 68)
	Low Agriculture	Agricultural Worker (cat. 69)
Occupation Grandfather		
S-E Agriculture	S-E Agriculture	
S-E non Agriculture	S-E non Agriculture	
High Managerial Supervisory Occ.	High Managerial & Supervisory	
Lower Services	Lower Services	
Lower Technical	Low Technical	All “Lower Technical” cat. but 67-68-69
	Lowest Technical	Unskilled Worker (cat. 67 & 68)
	Low Agriculture	Agricultural Worker (cat. 69)

Table A2: Description of the information used in *sample first*

Subject	Criteria	Justification
To be part of the sample	(v) must have both parents, i.e. (iii) and (iv), immigrants	By focusing on children of mixed couples (one immigrant and one native), the influence of the pre-migration status is mixed with the influence of the socio-economic background of the parent who is a native. It can then be that the relevant background for the children is the one of the native parent.
	(v) must have arrived before age 10	To make sure that they have been socialized in the environment characterized by $S_{p,2}$.
	(i) must have arrived after age 60 or not have emigrated to France [a]	Since TeO is a cross section, the variable indicating the occupation of the grandfather in 2008 could be his occupation in France if he had moved. To prevent this case, I keep families whose grandfather never moved to France or moved after age 60.
Status in France	I use the following categorization Managerial & S-E Non Agriculture, Supervisory & Low Services, Low Technical, Lower Agriculture and Lowest Technical Based on the occupation of the father, (iii) if (iii) is a man or of (iv) if (iii) is a woman.	
Status before migration	Parents: Occupation of (iii) or education level of (iii) Grandparents: Occupation of (i) (or (ii)) according to the following categorization: Managerial & Supervisory, S-E Non-Agriculture, S-E Agriculture, Low Services, Low Technical, Low Agriculture or education level of (i)	
Outcomes	Baccalauréat, being 18 or above	18 is a sensitive age to have finished high school.

Note: The categories (i) - (v) refer to Figure 1.

[a] Restriction implemented when looking at grandparents' characteristics

Table A3: Description of the information used in *sample second*

Subject	Criteria	Justification
To be part of the sample	(iii) must have both parent immigrants	By focusing on children of mixed couples (one immigrant and one native), the influence of the premigration status is mixed with the influence of the socio-economic background of the parent who is a native. It can then be that the relevant background for the children is the one of the native parent.
	(i) and (ii) have arrived after age 20	To have acquired human capital in the origin country
Status in France	Based on occupation of the father (i), I use the following categorization Managerial & S-E Non Agriculture, Supervisory & Low Services, Low Technical, Lower Agriculture and Lowest Technical	
Status before migration	Education of the parents (i) and (ii)	
Outcomes	Dropout and Baccalauréat, being 18 or above	18 is a sensitive age to have finished high school.
	Higher Education, being 25 or above	25 is a sensitive age to have finished university.
Parental Investment	I create several dummy variables if the child has been in a school different than the one of its neighborhood, if children report that either their father or their mother helped them sometimes or often with their homework, if children had a room of their own to study and if parents paid for private classes to their children	

Note: The categories (i) - (v) refer to Figure A1.

Table A4: Descriptive Statistics - *Sample second*

	Fathers	Mothers
	Birth Year	
25th percentile	1932	1935
Median	1939	1944
75th percentile	1946	1950
	Arrival Year	
25th percentile	1960	1962
Median	1967	1969
75th percentile	1972	1975
	Education	
< Primary School	840	924
Primary School	223	180
Secondary Education	29	45
Higher Education	67	47

Note : The observations are parents of second generation immigrants followed in *sample second*. I report for fathers (left column) and mothers (right column), the year of birth, the year of arrival in France and the education level. The entry 47 should be read as follows; among second generation immigrants, 47 have a mother with a higher education degree.

Table A5: Importance of Pre-Migration Background - Probit model

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.57***	0.46***	0.55***	0.53***
	(0.156)	(0.166)	(0.181)	(0.187)
Supervisory & Low Services	0.21	0.15	0.19	0.17
	(0.150)	(0.149)	(0.164)	(0.167)
S-E Agriculture	-0.09	-0.17	-0.16	-0.08
	(0.175)	(0.179)	(0.178)	(0.185)
Low Technical	-0.02	-0.11	-0.11	-0.14
	(0.146)	(0.150)	(0.159)	(0.156)
Low Agriculture	-0.16	-0.08	-0.09	-0.06
	(0.190)	(0.206)	(0.216)	(0.211)
Mean Outcome	0.58	0.58	0.58	0.58
Pseudo R-Squared	0.022	0.037	0.064	0.083
Nb of Observations	1175	1146	1146	1145
Chi-Square Pre-Migration	24.94	17.19	21.12	16.83
Chi-Square Post-Migration		11.34	6.55	8.29
Panel B: Grandfather Occupation				
Managerial & Supervisory	0.84***	0.73***	0.76***	0.75***
	(0.175)	(0.185)	(0.186)	(0.192)
S-E Non Agriculture	0.59***	0.49***	0.44**	0.44**
	(0.164)	(0.172)	(0.180)	(0.180)
S-E Agriculture	0.09	0.08	0.05	0.09
	(0.153)	(0.159)	(0.162)	(0.161)
Low Services	0.36*	0.30	0.29	0.29
	(0.190)	(0.193)	(0.196)	(0.191)
Low Technical	0.08	-0.01	-0.02	-0.04
	(0.172)	(0.181)	(0.181)	(0.176)
Low Agriculture	0.08	0.20	0.17	0.20
	(0.186)	(0.188)	(0.190)	(0.196)
Mean Outcome	0.58	0.59	0.59	0.58
Pseudo R-Squared	0.034	0.047	0.075	0.096
Nb of Observations	1560	1516	1516	1514
Chi-Square Pre-Migration	52.58	35.37	36.68	30.95
Chi-Square Post-Migration		18.28	13.45	13.17
Occupation Father ($S_{P,2}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Familly Controls	NO	NO	YES	YES
Origin FE	NO	NO	NO	YES

Note: This Table reports estimates of a probit model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (from the father's side) occupation. The second column controls for father's occupation in France. The third column adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects. The last column adds family controls (number of siblings, birth order and number of years since the father arrived in France). Each panel reports the χ^2-test for $\mathbb{H}_0 : S_{P,0} = 0$ (Chi-square Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (Chi-Square Post-Migration). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B)

Table A6: Importance of Pre-Migration Background - Sample Weights

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.21***	0.19***	0.18***	0.18***
	(0.064)	(0.065)	(0.068)	(0.070)
Supervisory & Low Services	0.12*	0.09	0.09	0.08
	(0.065)	(0.064)	(0.067)	(0.067)
S-E Agriculture	-0.03	-0.07	-0.07	-0.04
	(0.086)	(0.083)	(0.081)	(0.081)
Low Technical	0.02	-0.01	-0.02	-0.02
	(0.066)	(0.064)	(0.065)	(0.065)
Low Agriculture	-0.07	-0.04	-0.05	-0.02
	(0.085)	(0.091)	(0.093)	(0.087)
Mean Outcome	0.58	0.58	0.58	0.58
R-Squared	0.028	0.055	0.088	0.118
Nb of Observations	1175	1146	1146	1146
F-test Pre-Migration	4.12	3.18	3.06	2.41
F-test Post-Migration		2.39	1.55	2.09
Panel B: Grandfather Occupation				
Managerial & Supervisory	0.33***	0.30***	0.29***	0.29***
	(0.071)	(0.074)	(0.069)	(0.070)
S-E Non Agriculture	0.22***	0.19**	0.18**	0.19***
	(0.075)	(0.076)	(0.074)	(0.073)
S-E Agriculture	0.06	0.07	0.05	0.06
	(0.071)	(0.070)	(0.066)	(0.064)
Low Services	0.18*	0.17*	0.17*	0.17**
	(0.095)	(0.094)	(0.091)	(0.079)
Low Technical	0.04	0.01	0.01	0.01
	(0.077)	(0.078)	(0.073)	(0.071)
Low Agriculture	0.02	0.06	0.05	0.08
	(0.083)	(0.082)	(0.080)	(0.081)
Mean Outcome	0.59	0.59	0.59	0.59
R-Squared	0.048	0.065	0.097	0.126
Nb of Observations	1560	1516	1516	1515
F-test Pre-Migration	9.76	6.56	6.58	5.72
F-test Post-Migration		3.22	2.22	2.18
Occupation Father ($S_{P,2}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Origin FE	NO	NO	YES	YES
Family Controls	NO	NO	NO	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Results are weighted (using weights provided by TeO). Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (from the father's side) occupation. The second column controls for father's occupation in France. The third column adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects. The last column adds family controls (number of siblings, birth order and number of years since the father arrived in France). Each panel reports the F-test for $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (F-test Post-Migration). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B)

Table A7: Importance of Pre-Migration Background - Usual INSEE Categories

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
S-E Agricultural	-0.02	-0.06	-0.05	-0.02
	(0.062)	(0.063)	(0.059)	(0.063)
S-E non Agricultural	0.12*	0.10	0.14**	0.13*
	(0.066)	(0.067)	(0.067)	(0.067)
High Managerial	0.31***	0.22***	0.23***	0.23***
	(0.047)	(0.055)	(0.057)	(0.063)
Supervisory Occ.	0.12*	0.08	0.10*	0.11*
	(0.064)	(0.062)	(0.062)	(0.065)
Lower Services	0.07	0.07	0.08	0.07
	(0.061)	(0.062)	(0.062)	(0.062)
Mean Outcome	0.58	0.58	0.58	0.58
R-Squared	0.033	0.052	0.086	0.112
Nb of Observations	1175	1140	1140	1140
F-test Pre-Migration	9.64	3.80	4.04	2.86
F-test Post-Migration		3.21	2.25	2.39
Panel B: Grandfather Occupation				
S-E Agricultural	0.01	0.01	0.00	0.02
	(0.041)	(0.041)	(0.042)	(0.042)
S-E non Agricultural	0.20***	0.16***	0.14***	0.14***
	(0.043)	(0.044)	(0.046)	(0.046)
High Managerial	0.32***	0.22***	0.21***	0.19***
	(0.049)	(0.051)	(0.049)	(0.050)
Supervisory Occ.	0.23***	0.14**	0.17***	0.17**
	(0.063)	(0.064)	(0.061)	(0.067)
Lower Services	0.12**	0.08	0.08	0.08
	(0.059)	(0.057)	(0.058)	(0.055)
Mean Outcome	0.58	0.59	0.59	0.59
R-Squared	0.045	0.078	0.109	0.132
Nb of Observations	1560	1510	1510	1509
F-test Pre-Migration	13.42	5.69	5.62	4.51
F-test Post-Migration		13.90	10.26	8.42
Occupation Father ($S_{P,2}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Origin FE	NO	NO	YES	YES
Family Controls	NO	NO	NO	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (from the father's side) occupation. The second column controls for father's occupation in France. The third column adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects. The last column adds family controls (number of siblings, birth order and number of years since the father arrived in France). Each panel reports the F-test for $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (F-test Post-Migration). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B)

Table A8: Importance of Pre-Migration Background - Arriving at 24 y.o. or older

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.31***	0.25***	0.25***	0.23**
	(0.085)	(0.090)	(0.097)	(0.101)
Supervisory & Low Services	0.21**	0.18**	0.15	0.12
	(0.090)	(0.088)	(0.098)	(0.100)
S-E Agriculture	0.15	0.24*	0.16	0.12
	(0.142)	(0.124)	(0.125)	(0.113)
Low Technical	0.11	0.11	0.08	0.04
	(0.093)	(0.093)	(0.100)	(0.102)
Low Agriculture	-0.18	-0.25**	-0.32**	-0.35**
	(0.124)	(0.119)	(0.133)	(0.149)
Mean Outcome	0.60	0.61	0.61	0.61
R-Squared	0.060	0.091	0.147	0.179
Nb of Observations	494	487	487	487
F-test Pre-Migration	6.16	5.22	5.34	4.14
F-test Post-Migration		3.28	3.21	2.59
Panel B: Grandfather Occupation				
Managerial & Supervisory	0.29**	0.27**	0.22**	0.24**
	(0.117)	(0.120)	(0.108)	(0.115)
S-E Non Agriculture	0.18	0.18	0.10	0.11
	(0.119)	(0.122)	(0.114)	(0.119)
S-E Agriculture	0.06	0.12	0.02	0.02
	(0.118)	(0.119)	(0.113)	(0.116)
Low Services	0.21*	0.21*	0.16	0.17
	(0.125)	(0.124)	(0.120)	(0.121)
Low Technical	0.04	0.07	0.01	-0.01
	(0.135)	(0.136)	(0.127)	(0.133)
Low Agriculture	-0.01	0.12	0.06	0.04
	(0.147)	(0.148)	(0.140)	(0.155)
Mean Outcome	0.61	0.62	0.62	0.62
R-Squared	0.044	0.077	0.139	0.169
Nb of Observations	545	531	531	531
F-test Pre-Migration	3.23	1.53	2.34	2.68
F-test Post-Migration		4.16	3.45	4.31
Occupation Father ($S_{P,2}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Familly Controls	NO	NO	YES	YES
Origin FE	NO	NO	NO	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (from the father's side) occupation. The second column controls for father's occupation in France. The third column adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects. The last column adds family controls (number of siblings, birth order and number of years since the father arrived in France). Each panel reports the F-test for $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (F-test Post-Migration). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B). In both cases father emigrated at the age of 24 or older.

Table A9: Importance of Pre-Migration Background - Only Immigrants without children

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.21***	0.19***	0.21***	0.19**
	(0.066)	(0.066)	(0.072)	(0.075)
Supervisory & Low Services	0.09	0.06	0.08	0.06
	(0.067)	(0.067)	(0.070)	(0.071)
S-E Agriculture	-0.03	-0.08	-0.07	-0.05
	(0.075)	(0.076)	(0.075)	(0.077)
Low Technical	-0.04	-0.09	-0.09	-0.10
	(0.067)	(0.068)	(0.068)	(0.066)
Low Agriculture	-0.05	-0.04	-0.05	-0.03
	(0.087)	(0.093)	(0.097)	(0.094)
Mean Outcome	0.59	0.59	0.59	0.59
R-Squared	0.030	0.050	0.090	0.121
Nb of Observations	848	827	827	827
F-test Pre-Migration	4.64	4.77	5.19	4.05
F-test Post-Migration		1.88	1.16	1.20
Panel B: Grandfather Occupation				
Managerial & Supervisory	0.33***	0.29***	0.31***	0.29***
	(0.068)	(0.074)	(0.072)	(0.072)
S-E Non Agriculture	0.24***	0.21***	0.19**	0.18**
	(0.069)	(0.073)	(0.076)	(0.073)
S-E Agriculture	0.04	0.03	0.02	0.03
	(0.067)	(0.070)	(0.071)	(0.068)
Low Services	0.15*	0.13	0.12	0.12
	(0.083)	(0.085)	(0.086)	(0.080)
Low Technical	0.04	0.00	-0.00	-0.00
	(0.076)	(0.080)	(0.078)	(0.073)
Low Agriculture	0.03	0.05	0.04	0.04
	(0.082)	(0.085)	(0.086)	(0.084)
Mean Outcome	0.59	0.59	0.59	0.59
R-Squared	0.051	0.061	0.101	0.141
Nb of Observations	1221	1192	1192	1191
F-test Pre-Migration	10.00	6.92	8.24	6.02
F-test Post-Migration		1.67	1.18	0.85
Occupation Father ($S_{P,2}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Origin FE	NO	NO	YES	YES
Family Controls	NO	NO	NO	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (from the father's side) occupation. The second column controls for father's occupation in France. The third column adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects. The last column adds family controls (number of siblings, birth order and number of years since the father arrived in France). Each panel reports the F-test for $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (F-test Post-Migration). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B). In both cases, children were born after the father arrived in France.

Table A10: Importance of Pre-Migration Background - Using First Occupation in France

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.21***	0.16**	0.18***	0.18**
	(0.056)	(0.064)	(0.069)	(0.069)
Supervisory & Low Services	0.08	0.07	0.09	0.09
	(0.058)	(0.063)	(0.065)	(0.067)
S-E Agriculture	-0.03	-0.02	-0.01	0.01
	(0.070)	(0.072)	(0.074)	(0.077)
Low Technical	-0.01	-0.01	-0.01	-0.02
	(0.058)	(0.064)	(0.066)	(0.065)
Low Agriculture	-0.06	-0.04	-0.03	-0.03
	(0.076)	(0.080)	(0.082)	(0.080)
Mean Outcome	0.58	0.58	0.58	0.58
R-Squared	0.028	0.038	0.073	0.094
Nb of Observations	1175	1156	1156	1156
F-test Pre-Migration	5.75	2.42	2.91	2.44
F-test Post-Migration		1.69	1.20	0.84
Panel B: Grandfather Occupation				
Managerial & Supervisory	0.31***	0.25***	0.25***	0.25***
	(0.063)	(0.067)	(0.064)	(0.066)
S-E Non Agriculture	0.23***	0.20***	0.18***	0.18***
	(0.063)	(0.063)	(0.063)	(0.063)
S-E Agriculture	0.03	0.06	0.05	0.06
	(0.061)	(0.061)	(0.060)	(0.059)
Low Services	0.14*	0.13*	0.13*	0.12*
	(0.074)	(0.074)	(0.072)	(0.070)
Low Technical	0.03	0.03	0.02	0.02
	(0.069)	(0.069)	(0.067)	(0.064)
Low Agriculture	0.03	0.07	0.06	0.06
	(0.074)	(0.074)	(0.072)	(0.073)
Mean Outcome	0.58	0.59	0.59	0.59
R-Squared	0.045	0.059	0.095	0.116
Nb of Observations	1560	1532	1532	1531
F-test Pre-Migration	10.25	5.01	4.94	4.26
F-test Post-Migration		4.68	4.39	2.89
Occupation Father ($S_{P,1}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Origin FE	NO	NO	YES	YES
Family Controls	NO	NO	NO	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (from the father's side) occupation. The second column controls for father's first occupation in France. The third column adds individual controls (age and gender of the child, age of the father at the time of the interview) and origin fixed effects. The last column adds family controls (number of siblings, birth order and number of years since the father arrived in France). Each panel reports the F-test for $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,1} = 0$ (F-test Post-Migration). The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B)

Table A11: Importance of Pre-Migration Background - Sample Second

	(1)	(2)	(3)	(4)
	Panel A: Baccalauréat			
Education Father	0.016***	0.015***	0.013***	0.012***
	(0.0037)	(0.0039)	(0.0040)	(0.0040)
Education Mother	0.024***	0.024***	0.024***	0.020***
	(0.0040)	(0.0041)	(0.0041)	(0.0041)
Mean Outcome	0.51	0.51	0.51	0.51
R-Squared	0.109	0.116	0.168	0.201
Nb of Observations	1146	1136	1136	1136
F-test Pre-Migration	123.26	81.40	63.01	41.66
F-test Post-Migration		2.46	2.44	2.33
	Panel B: Not Dropping Out			
Education Father	0.009***	0.009***	0.010***	0.009***
	(0.0024)	(0.0025)	(0.0026)	(0.0026)
Education Mother	0.005*	0.005*	0.003	0.001
	(0.0027)	(0.0027)	(0.0029)	(0.0029)
Mean Outcome	0.86	0.87	0.87	0.87
R-Squared	0.028	0.029	0.054	0.099
Nb of Observations	1146	1136	1136	1136
F-test Pre-Migration	30.85	19.32	17.60	11.04
F-test Post-Migration		0.85	0.92	0.96
	Panel C: Higher Education Degree			
Education Father	0.017***	0.015***	0.014***	0.013***
	(0.0040)	(0.0042)	(0.0042)	(0.0043)
Education Mother	0.019***	0.019***	0.019***	0.016***
	(0.0044)	(0.0044)	(0.0045)	(0.0046)
Mean Outcome	0.31	0.31	0.31	0.31
R-Squared	0.102	0.111	0.137	0.164
Nb of Observations	1048	1041	1041	1041
F-test Pre-Migration	60.60	43.48	34.63	24.90
F-test Post-Migration		1.63	1.75	1.39
Occupation Father ($S_{P,2}$)	NO	YES	YES	YES
Individual Controls	NO	NO	YES	YES
Origin FE	NO	NO	YES	YES
Familly Controls	NO	NO	NO	YES

Note: This Table reports estimates of a linear probability model; in panel A the outcome is a dummy variable for having obtained the baccalauréat, in Panel B one for not having dropped out and in Panel C for having obtained a higher education (at least college degree). Parents' education are measured in years. The second column controls for father's occupation in France. The third column adds individual controls (age and gender of the child) and origin fixed effects. The last column adds family controls (number of siblings and number of years since the father arrived in France). Each panel reports the F-test for $\mathbb{H}_0 : S_{P,0} = 0$ (F-test Pre-Migration) and $\mathbb{H}_0 : S_{P,2} = 0$ (F-test Post-Migration). The observations are second generation immigrants, whose both father and mother arrived in France after age 20.

Table A12: Importance of pre-Migration Background - Heterogeneity - Probit

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.56***	0.44**	0.44**	0.46
	(0.194)	(0.216)	(0.216)	(0.283)
Supervisory & Low Services	0.11	-0.03	-0.03	-0.45
	(0.161)	(0.192)	(0.192)	(0.281)
S-E Agriculture	-0.12	-0.05	0.00	0.20
	(0.184)	(0.199)	(0.199)	(0.286)
Low Technical	-0.07	-0.03	-0.04	0.02
	(0.157)	(0.177)	(0.177)	(0.326)
Low Agriculture	-0.24	-0.22	-0.23	-0.38
	(0.194)	(0.202)	(0.209)	(0.329)
Mean Outcome	0.55	0.52	0.52	0.47
Pseudo R-Squared	0.017	0.010	0.010	0.032
Nb of Observations	982	767	753	297
Panel B: Grandfather (of the father) Occupation				
Managerial & Supervisory	0.85***	0.78***	0.78***	1.02***
	(0.197)	(0.254)	(0.254)	(0.368)
S-E Non Agriculture	0.68***	0.62***	0.62***	1.03***
	(0.188)	(0.211)	(0.211)	(0.364)
S-E Agriculture	0.13	0.12	0.15	0.31
	(0.164)	(0.181)	(0.182)	(0.267)
Low Services	0.31	0.27	0.27	0.41
	(0.209)	(0.237)	(0.237)	(0.306)
Low Technical	0.30	0.23	0.22	0.10
	(0.186)	(0.224)	(0.225)	(0.346)
Low Agriculture	0.06	0.05	0.05	0.20
	(0.196)	(0.208)	(0.208)	(0.320)
Mean Outcome	0.56	0.52	0.52	0.50
Pseudo R-Squared	0.033	0.024	0.023	0.048
Nb of Observations	1253	945	928	375
Managerial & S-E Non Agriculture	NO	NO	NO	NO
Supervisory & Low Services	YES	NO	NO	NO
S-E Agriculture	YES	YES	NO	NO
Low Technical	YES	YES	YES	NO
Lowest Technical	YES	YES	YES	YES
Low Agriculture	YES	YES	YES	YES

Note: This Table reports estimates of a probit model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (of the father) occupation. The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B). Each column excludes observations based on father's occupation in France, i.e. $S_{P,2}$. Column 1 to 4 successively drops immigrants whose father is "Managerial & S-E Non Agriculture", "Supervisory & Low Services", "S-E Agriculture" and "Low Technical".

Table A13: Importance of pre-Migration Background - Heterogeneity - Weights

	(1)	(2)	(3)	(4)
Panel A: Father Pre-Migration Occupation				
Managerial & S-E Non Agriculture	0.20***	0.20**	0.20**	0.20*
	(0.076)	(0.090)	(0.090)	(0.113)
Supervisory & Low Services	0.11	0.13	0.13	-0.12
	(0.069)	(0.088)	(0.088)	(0.116)
S-E Agriculture	-0.04	-0.03	-0.00	0.14
	(0.090)	(0.091)	(0.092)	(0.129)
Low Technical	0.01	0.03	0.03	0.06
	(0.070)	(0.079)	(0.079)	(0.134)
Low Agriculture	-0.10	-0.07	-0.08	-0.11
	(0.086)	(0.088)	(0.090)	(0.135)
Mean Outcome	0.56	0.52	0.52	0.46
R-Squared	0.025	0.023	0.022	0.040
Nb of Observations	982	767	753	297
Panel B: Grandfather (of the father) Occupation				
Managerial & Supervisory	0.34***	0.37***	0.37***	0.38***
	(0.079)	(0.089)	(0.089)	(0.125)
S-E Non Agriculture	0.23***	0.23**	0.23**	0.28
	(0.087)	(0.095)	(0.095)	(0.172)
S-E Agriculture	0.06	0.08	0.09	0.11
	(0.077)	(0.077)	(0.077)	(0.101)
Low Services	0.16	0.19	0.19	0.20
	(0.107)	(0.118)	(0.118)	(0.124)
Low Technical	0.10	0.06	0.05	0.03
	(0.084)	(0.092)	(0.092)	(0.130)
Low Agriculture	-0.00	0.02	0.02	0.08
	(0.089)	(0.087)	(0.087)	(0.121)
Mean Outcome	0.57	0.53	0.54	0.50
R-Squared	0.043	0.038	0.038	0.046
Nb of Observations	1253	945	928	375
Managerial & S-E Non Agriculture	NO	NO	NO	NO
Supervisory & Low Services	YES	NO	NO	NO
S-E Agriculture	YES	YES	NO	NO
Low Technical	YES	YES	YES	NO
Lowest Technical	YES	YES	YES	YES
Low Agriculture	YES	YES	YES	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Results are weighted (using weights provided by TeO). Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (of the father) occupation. The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B). Each column excludes observations based on father's occupation in France, i.e. $S_{P,2}$. Column 1 to 4 successively drops immigrants whose father is "Managerial & S-E Non Agriculture", "Supervisory & Low Services", "S-E Agriculture" and "Low Technical".

Table A14: Importance of pre-Migration Background - Heterogeneity - Usual INSEE Categories

	(1)	(2)	(3)
Panel A: Father Pre-Migration Occupation			
S-E Agriculture	-0.01	0.00	0.02
	(0.065)	(0.065)	(0.068)
S-E non Agriculture	0.20***	0.17**	0.18**
	(0.070)	(0.077)	(0.079)
High Managerial	0.33***	0.28***	0.16
	(0.052)	(0.079)	(0.105)
Supervisory Occ.	0.13*	0.10	-0.04
	(0.071)	(0.080)	(0.106)
Lower Services	0.05	0.06	0.07
	(0.064)	(0.065)	(0.069)
Mean Outcome	0.58	0.56	0.53
R-Squared	0.038	0.019	0.010
Nb of Observations	1022	955	821
Panel B: Grandfather (of the father) Occupation			
S-E Agriculture	0.01	0.01	0.03
	(0.044)	(0.044)	(0.047)
S-E non Agriculture	0.23***	0.21***	0.21***
	(0.048)	(0.052)	(0.058)
High Managerial	0.32***	0.30***	0.23**
	(0.052)	(0.064)	(0.089)
Supervisory Occ.	0.23***	0.24***	0.23**
	(0.064)	(0.070)	(0.088)
Lower Services	0.11*	0.08	0.09
	(0.063)	(0.067)	(0.074)
Mean Outcome	0.59	0.56	0.53
R-Squared	0.051	0.039	0.027
Nb of Observations	1342	1221	1021
S-E Agricultural	NO	NO	NO
S-E non Agricultural	NO	NO	NO
High Managerial	YES	NO	NO
Supervisory Occ.	YES	YES	NO
Lower Services	YES	YES	YES
Lower Technical	YES	YES	YES

Note: This Table reports estimates of a linear probability model where the outcome is a dummy variable for having obtained the baccalauréat. Panel A measures $S_{P,0}$ with father's pre-migration occupation, while panel B uses grandfather's (of the father) occupation. The observations are (adult) children of first generation immigrants, whose father reported having a job before migration (panel A), whose grandfather stayed in the origin country or migrated after 60 y.o. (panel B). Each column excludes observations based on father's occupation in France, i.e. $S_{P,2}$. Column 1 to 3 successively drops immigrants whose father is "S-E Agriculture" or "S-E Non Agriculture", "High Managerial" and "Supervisory Occupation".

Table A15: Grand-parents' education: Effect for immigrants and natives - Probit

	Immigrants					Natives				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Education Father	0.032***		0.034***		0.024***	0.060***		0.085***		0.058***
	(0.0066)		(0.0068)		(0.0072)	(0.0107)		(0.0106)		(0.0111)
Education Mother	0.035***			0.038***	0.028***	0.084***			0.102***	0.082***
	(0.0075)			(0.0075)	(0.0081)	(0.0119)			(0.0118)	(0.0122)
Gd Father - Mother		0.025**	0.026***		0.013		0.033*	0.020		0.006
		(0.0125)	(0.0091)		(0.0127)		(0.0169)	(0.0128)		(0.0171)
Gd Father - Father		0.037***	0.035***		0.017		0.009	0.032**		0.000
		(0.0131)	(0.0104)		(0.0140)		(0.0231)	(0.0130)		(0.0235)
Gd Mother - Mother		0.043***		0.040***	0.018		0.036*		0.026*	0.004
		(0.0161)		(0.0108)	(0.0159)		(0.0211)		(0.0143)	(0.0198)
Gd Mother - Father		0.033*		0.038***	0.018		0.066**		0.020	0.011
		(0.0187)		(0.0144)	(0.0189)		(0.0270)		(0.0145)	(0.0280)
Nb of Observations	2329	2329	2329	2329	2329	1329	1329	1329	1329	1329
Pseudo R-Squared	0.057	0.045	0.053	0.053	0.062	0.128	0.033	0.084	0.104	0.128
χ^2 test: Grandparent Effect		67.684	13.928	16.070	10.185		28.211	6.089	3.483	0.543
P-value		0.000	0.001	0.000	0.037		0.000	0.048	0.175	0.969

Note: This Table reports estimates from probit models where the outcome is having obtained the baccalauréat. All regressions control for age and gender of the young adult (child of immigrants and natives). The first five columns report results on immigrants, the five last on natives. All covariates of interest refer to years of education (of parents or grandparents). Grandparents' education is interacted with the gender of the parent being interviewed to allow for the effect to differ between grandparents from the mother's or father's side. The table reports the χ^2-test (and associated p-values) of the null: all grandparents coefficients in the column are zero. Standard errors are clustered at the family level.

Table A16: Grand-parents' education: Effect for immigrants and natives - Sample Weights

	Immigrants					Natives				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Education Father	0.012***		0.013***		0.010***	0.022***		0.030***		0.022***
	(0.0029)		(0.0028)		(0.0031)	(0.0037)		(0.0036)		(0.0039)
Education Mother	0.013***			0.015***	0.011***	0.025***			0.033***	0.025***
	(0.0032)			(0.0031)	(0.0034)	(0.0041)			(0.0040)	(0.0042)
Gd Father - Mother		0.012**	0.007**		0.007		0.009	0.005		0.000
		(0.0051)	(0.0033)		(0.0049)		(0.0068)	(0.0039)		(0.0052)
Gd Father - Father		0.014***	0.013***		0.006		0.005	0.008*		0.003
		(0.0044)	(0.0034)		(0.0047)		(0.0093)	(0.0046)		(0.0086)
Gd Mother - Mother		0.007		0.008**	-0.003		0.012		0.008*	0.000
		(0.0063)		(0.0039)	(0.0061)		(0.0083)		(0.0046)	(0.0063)
Gd Mother - Father		0.013**		0.013***	0.006		0.018*		0.006	-0.003
		(0.0063)		(0.0047)	(0.0064)		(0.0100)		(0.0050)	(0.0091)
Nb of Observations	2329	2329	2329	2329	2329	1329	1329	1329	1329	1329
R-Squared	0.075	0.054	0.069	0.065	0.080	0.140	0.032	0.102	0.106	0.140
F-test: Grandparent Effect		18.062	7.162	4.604	1.951		5.606	1.484	1.466	0.040
P-value		0.000	0.001	0.010	0.100		0.000	0.228	0.232	0.997

Note: This Table reports estimates from linear probability models where the outcome is having obtained the baccalauréat. Results are weighted (using weights provided by TeO). All regressions control for age and gender of the young adult (child of immigrants and natives). The first five columns report results on immigrants, the five last on natives. All covariates of interest refer to years of education (of parents or grandparents). Grandparents' education is interacted with the gender of the parent being interviewed to allow for the effect to differ between grandparents from the mother's or father's side. The table reports the F-test (and associated p-values) of the null: all grandparents coefficients in the column are zero. Standard errors are clustered at the family level.

Table A17: Skill downgrading among first generation immigrants - Arriving after 24

		Occupation at Arrival					
		Managerial & S-E Non Agriculture	Supervisory & Low Services	Low Technical	Lowest Technical	Low Agriculture	Total
Occ. before Migration	Managerial & S-E Non Agriculture	40.5	15.5	29.8	11.9	2.4	84
		(5.36)	(3.95)	(5.00)	(3.54)	(1.67)	
	Supervisory & Low Services	9.6	47.0	21.7	20.5	1.2	83
		(3.24)	(5.49)	(4.53)	(4.44)	(1.20)	
	S-E Agriculture	0.0	7.7	46.2	30.8	15.4	13
		(0.00)	(7.40)	(13.85)	(12.82)	(10.02)	
	Low Technical	0.0	13.9	56.9	26.4	2.8	72
		(0.00)	(4.08)	(5.85)	(5.20)	(1.94)	
	Lowest Technical	2.7	10.8	16.2	62.2	8.1	37
		(2.67)	(5.11)	(6.07)	(7.99)	(4.50)	
	Low Agriculture	0.0	0.0	25.0	37.5	37.5	8
		(0.00)	(0.00)	(15.34)	(17.15)	(17.15)	
	Total	43	67	98	76	13	

Note: This Table reports the transition between occupation before migration in the origin country (rows) and first occupation in France (columns). The Table reports conditional probabilities, the last row and the last column report raw numbers. The observations are fathers of (adult) second generation immigrants followed in sample first who arrived in France at the age of 24 years old or older. Numbers in parenthesis are standard deviation.

Table A18: Downgrading - Robustness to Time of of Arrival

	Occupation at Arrival			
Managerial & S-E Non Agriculture	0.35***	0.36***	0.32***	0.32***
	(0.033)	(0.035)	(0.037)	(0.037)
Supervisory & Low Services	0.07**	0.08**	0.04	0.04
	(0.031)	(0.032)	(0.033)	(0.033)
S-E Agriculture	-0.01	-0.02	-0.02	-0.01
	(0.040)	(0.040)	(0.040)	(0.040)
Low Technical	-0.00	-0.00	-0.02	-0.02
	(0.031)	(0.032)	(0.033)	(0.033)
Low Agriculture	0.01	0.02	0.03	0.04
	(0.044)	(0.045)	(0.045)	(0.045)
Birth year FE	NO	YES	YES	YES
Arrival year FE	NO	NO	YES	YES
Origin FE	NO	NO	NO	YES
Mean Outcome	0.09	0.09	0.09	0.09
R-Squared	0.21	0.25	0.34	0.36
Nb of Observations	614	614	614	614

Note : This Table reports the results of a regression where the dependent variable is a dummy for having a "high" occupation (Managerial, S-E Non-Agriculture and Supervisory) immediately following migration. The main regressor is a categorical variable for pre-migration occupation. The baseline category is having worked as a "Lowest Technical" in the origin country. The first column does not include any control, the second includes year of birth fixed effects. The third column includes year of birth and year at arrival fixed effects. The fourth column includes all the controls mentioned and origin fixed effects. The observations are fathers of (adult) second generation immigrants followed in sample first, who reported having a job before migrating.

Table A19: Parental Investments - Robustness - Other Outcomes

	Strategy	Help Homework	Room to study	Private classes
		Panel A: Not Dropping Out		
Immigrants	0.03	0.04*	0.04**	0.09***
	(0.024)	(0.021)	(0.020)	(0.019)
Natives	-0.00	-0.02	0.00	0.05**
	(0.030)	(0.027)	(0.027)	(0.022)
Mean Outcome	0.87	0.86	0.86	0.86
R-Squared	0.04	0.05	0.06	0.06
Nb of Observations	1607	1659	1688	1688
P-value	0.29	0.03	0.09	0.06
		Panel B: Higher Education Degree		
Immigrants	0.11**	0.13***	-0.00	0.17***
	(0.041)	(0.035)	(0.028)	(0.047)
Natives	0.00	0.04	0.03	0.14**
	(0.061)	(0.040)	(0.039)	(0.061)
Individual Controls	YES	YES	YES	YES
Origin FE	YES	YES	YES	YES
Mean Outcome	0.32	0.33	0.33	0.33
R-Squared	0.09	0.10	0.09	0.10
Nb of Observations	1422	1471	1496	1496
P-value	0.15	0.05	0.32	0.75

Note: This Table presents the results of estimating equation 2 where the outcome is not dropping out (panel A) and obtaining a higher education level (panel B). Estimation is performed on a sample of second generation immigrants and natives. The rows referred to as Immigrant and Natives are the coefficients associated with investing and being an immigrant or a native. The four investments are sending children to a school outside the neighborhood "Strategy", helping with homework "Help Homework", providing a room where children can study alone "Room to study" and paying for private classes "Private Classes". Controls include age, gender (of the child and of the parent being interviewed), number of siblings, occupation of the father in France and origin fixed effects. Each column reports the p-value associated with the hypothesis of equality between the two coefficients reported.