Immigration and the Occupational Choice of Natives: a Factor Proportions Approach*

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Abstract

This paper evaluates the impact of immigration on the labor market outcomes of natives in France over the period 1962-1999. Combining large (up to 25%) extracts from six censuses and data from Labor Force Surveys, we exploit the variation in the immigrant share across education/experience cells and over time to identify the impact of immigration. In the Borjas (2003) specification, we find that a 10% increase in immigration increases native wages by 3%. However, as the number of immigrants and the number of natives are positively and strongly correlated across cells, the immigrant share may not be a good measure of the immigration shock. When the log of natives and the log of immigrants are used as regressors instead, the impact of immigration on natives' wages is still positive but much smaller, and natives' wages are negatively related to the number of natives. To understand this asymmetry and the positive impact of immigration on wages, we explore the link between immigration and the occupational distribution of natives within education/experience cells. Our results suggest that immigration leads to the reallocation of natives to better-paid occupations within education/experience cells.

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Introduction

Recent years have seen a renewed interest in the research on the impact of immigration on the labor market outcomes of natives. Until the 1990s, the methodology exploited the variation in the share of immigrants across geographical locations.[1] After Borjas, Freeman and Katz (1997) underlined some potential problems of this approach,[2] a new strand of literature has proposed to measure the impact of immigration by relating the variation over time in the number of specific groups of immigrants with the outcomes of the natives with similar characteristics.

In her study of mass-migration of Russian workers in Israel in the 1990s, Friedberg (2001) chooses occupation as the relevant dimension and finds no evidence of a negative relation between the inflow of immigrants to certain occupations and the wage growth of natives working in the same occupation. This is interpreted as evidence for the existence of immigrant-native complementarity within occupations.

In Peri and Sparber (2009) immigrants and natives with little educational attainment in the U.S. are assumed to belong to the same group if they perform the same type of production tasks in a given state. Again, immigration does not have a large, adverse effect on the wage of less educated natives, mainly because natives respond to immigration by specializing in language intensive tasks —for which they have a comparative advantage and which are better remunerated than manual-physical tasks.

The dimension that has attracted most attention is the education/experience dimension, as proposed initially by Borjas (2003), which assumes that natives and immigrants within education/experience cells are perfect substitutes, and uses the variation in the immigrant share at the cell level over time to identify the impact of immigration. Using this approach, Borjas (2003) finds a large negative impact of immigration on natives'wages.[3] A series of papers have sug-

[1] See e.g. Card (1990), Altonji and Card (1991) or Hunt (1992). The consensus was that the effect of immigration on natives was small, see for instance Friedberg and Hunt (1995) or Borjas (1994).

[2] Borjas et al. (1997) argues that this approach may understate the impact of immigration for two important reasons. First, natives may respond to immigrant inflows by moving out to other locations, which would diffuse the impact of migration across locations but would not be captured in a spatial correlation approach. Second, immigrants may choose the best locations, which would tend to generate a positive correlation between immigration and labor market outcomes. For a paper treating these biases, see Pischke and Velling (1997). Recent evidence on the response of natives to immigrations flows is relatively mixed, see Card and DiNardo (2000), Card (2001), and Borjas (2006).

[3] Aydemir and Borjas (2007) finds also a large negative impact for Canada, Mexico, and the U.S. However, the same approach applied to European countries (see Bonin, 2005, for Germany; Carrasco, Jimeno and Ortega,

gested different modifications or refinements of Borjas (2003) keeping the analysis along the education/experience dimension. In particular, Card (2009) argues that, in the case of the U.S., a model with four groups of education (high-school dropouts, high-school graduates, individuals with some college, and college graduates) as in Borjas (2003) or Borjas and Katz (2007) does not fit well the data. In addition, Manacorda, Manning, and Wadsworth (2010) for the U.K. and Ottaviano and Peri (2007, 2008) and the U.S. argue that natives and immigrants are imperfect substitutes within education/experience cells. However, Borjas, Grogger and Hanson (2008) argues that one cannot reject that immigrants and natives are perfect substitutes in the U.S. case.

This paper contributes to the literature by explicitly identifying occupations as an important source of imperfect substitutability between natives and immigrants *within* education/experience cells. Indeed, we show that in France the average wage within a given education/experience cell strongly depends on the allocation across occupations of the individuals in the cell. Then, we provide evidence that the arrival of immigrants to a particular education/experience cell results in a reallocation of natives within the cell towards better paid occupations, which is likely to be at the origin of the positive impact of immigration on natives' wages identified in the regressions where occupations are not accounted for.

We first follow Borjas (2003) to evaluate the impact of immigration in France for the period 1962-1999.[4] In contrast with other European studies, our sample size is large —25% of the Census population for most of the censuses available in this period. In addition, our long time span allows for a lot of variation in the proportion of immigrants over time. In the baseline specification à la Borjas (2003), we find that a 10% increase in the immigrant share is associated with wages *higher* by 3%.[5] Similar results are found when the immigrant share is

2008, for Spain; and Dustmann, Fabbri and Preston, 2005 for the U.K.) has produced much smaller impacts of immigration. Some of these studies have been criticized by Aydemir and Borjas (2011) on the basis that they typically use a relatively small sample to compute the share of immigrants per education/experience cell.

[4]To the best of our knowledge, this is the first paper applying a factor proportion approach to France. Hunt (1992) studies the impact of immigration on natives exploiting the spatial variation in the settlement of the repatriates from Algeria in 1962.

[5]The impact is still positive and significant but the coefficients are smaller when a geographical dimension is added. Ortega (2000) proposes a theoretical rationale for why immigration may increase native wages and lower native unemployment.

instrumented by its lagged values at the cohort level to account for a potential endogeneity of immigrant inflows to education/experience cells.

Next, we show that the number of immigrants and the number of natives are highly positively correlated across education/experience/time cells. As a result, even if the number of natives enters the immigrant share in the denominator, the immigrant share is actually positively correlated to the number of natives. For this reason, the immigrant share may not be a good measure of the immigration shock. When the log of natives and the log of immigrants are used as regressors instead, the impact of immigration on natives' wages is shown to be still positive but much smaller, and natives' wages are shown to be negatively related to the number of natives.

To understand the positive impact of immigration on wages and the asymmetry in the effects of the number of natives and the number of immigrants, we explore the link between immigration and the occupational distribution of natives within education/experience cells. We consider between 30 and 300 occupations, defined using the interaction between professional status and industry classifications at different aggregation levels. We proceed by first estimating occupational wage premia for each of the occupations using separate regression models for each year with flexible controls for education and experience. From this, we compute the average occupational premium for each education/experience cell.

In principle, immigrants can simultaneously affect wages within occupations and the allocation of natives across occupations. To test whether immigration triggers a reallocation of natives across occupations, we include the occupational premium at the education/experience level as an explanatory variable for the wage of natives, together with the log of natives and the log of immigrants. If immigrants influence the occupational distribution of workers, the error term might be correlated with our occupational premium. To deal with this issue, we instrument the current occupational premium using a shift-share model constructed using the past occupational distributions of the cohort. We also use the past change in the occupational distribution at the cohort level as an instrument. This last instrument is valid if the initial occupational distributions are unrelated with future fluctuations or changes in the contemporary immigrant share over time. We find the wage differences within education/experience cells to be strongly related to differences in the occupational distribution of workers across cells. When accounting for the potential endogeneity of the occupational premium, we find a strong positive (resp. negative) effect of the number of immigrants (resp. the number of natives) on the wage, while the point estimates of the occupational premium are generally not significant anymore. At the national level, natives in cells with more immigrants tend thus to work in better-paid occupations than other natives.

However, these results may come from immigrants self-selecting to the same best-paid occupations as the natives from their same education/experience cell. For this reason, following Peri and Sparber (2009), we construct a measure of the relative occupational premium of natives versus immigrants within each education/experience cell. This relative occupational premium thus indicates the distance between the respective average job quality of immigrants and natives within education/experience cells. We find that the relative premium of natives increases with the number of immigrants while the occupational premium of immigrants decreases with the immigrant share. These results not only suggest that the occupational choices of natives and immigrants are different but that they are related.

Finally, we extend the analysis by adding a geographical dimension, which enables us to use the settlement patterns of immigrants as an alternative instrument for migration shocks across cells. We show that the results on the relative premium and the specialization of immigrants still hold, and that the positive (resp. negative) correlation between the occupational premium of natives and the number of immigrants (resp. natives) also holds at the regional level.

Section 1 describes the data and the main trends of immigration into France, Section 2 presents the econometric models, and Section 3 presents the results.

1 Data

We use data from six successive French censuses from 1962 to 1999 (1962, 1968, 1975, 1982, 1990, and 1999) to compute the number of immigrants and natives with a given level of education and labor market experience in each year. Since the French Census does not include information on income or wages, we rely on other surveys to construct our wage sample.[6] For

[6]We are thus following Katz and Murphy (1992) in constructing separate count and wage samples.

Table 1: Distribution of Educational Attainment in the French Population (percentage)

	1962	1968	1975	1982	1990	1999
Primary School	78.3	68.3	56.5	50.2	39.5	24.5
Secondary School	13.0	20.1	26.1	28.9	35.9	40.7
High School	4.9	7.5	9.5	11.2	11.2	14.7
College	3.7	4.2	7.8	9.7	13.4	20.1

Notes: Tabulations include men aged between 18 and 64 years old, not enrolled in school nor in military.

1982, 1990, and 1999, the best available information on wages is given by the corresponding French Labor Force Survey (LFS), which provides information since 1982 on monthly wages in the month preceding the survey month. For 1962, we use the data on annual wage income from the 1964 *Enquête Formation et Qualification Professionnelles* (FQP). Finally, as no information on wages is available for 1968 and 1975, the best approximation is the 1969 and 1976 data available in the 1970 and 1977 FQPs. As we use labor force surveys to compute wages, we do not include immigrants' wages in the analysis, due to the small number of observations by education/experience cell.

As common in the literature,[7] we restrict our attention to males aged 18-64. Men are classified into four educational groups depending on their highest attained diploma: no education or primary education (less than six years of education), secondary education (between 6 and 9 years), high school (11 or 12 years), and college (at least 14 years).[8]

Table 1 shows the evolution of the educational composition of the male French labor force over the period. The most striking feature is that the share of individuals with only primary education decreased from about 80% in 1962 to 24.5% in 1999, while the share of individuals with high-school or college diploma rapidly increased.

Labor market experience is measured as the age of the individual minus the entry age into the labor market. As the entry age into the labor market is not observed, we assume that individuals with primary, secondary, high school, and college education enter the labor market respectively when 15, 16, 19, and 24 years old. In addition, we restrict the analysis to individ-

[7]See for instance Borjas (2003) or Manacorda et al. (2010)

[8]A detailed match between French diplomas reported across censuses and these educational groups is provided in Appendix 1. We follow here the diploma classification which serves as a reference for French labor relations. The distinction between individuals with some college ("Bac+2" and "Bac+3") and college graduates frequently used in the literature is only available from the 1982 Census, so we cannot create a category "some college" for the entire period. However, given the relatively low educational level of the French labor force at the beginning of the sixties, such distinction is not fundamental for the period of time under consideration.

uals between 1 and 40 years of labor market experience. For each education level, we group individuals in 5-years experience groups.

Following Borjas (2003), the immigration shock experienced by natives with education i, experience j at year t could be measured by p_{ijt}, the relative share of immigrants among all individuals in the cell:

$$p_{ijt} = M_{ijt}/(M_{ijt} + N_{ijt}), \tag{1}$$

where N_{ijt} and M_{ijt} denote respectively the number of natives and the number of immigrants in the corresponding cell. Table 2 reports p_{ijt} for the male population between 1962 and 1999 as computed from the Census data. From this table, it appears that the evolution of the share of immigrants over time greatly varies across educational groups. For individuals with primary school education, the share first rises and then declines. [9]

Instead, the share of immigrants among individuals with secondary education rises over the period, although not always in a monotonous fashion. Finally, for higher educational levels (high school and college graduates), the share of immigrants generally decreases until 1982 and then rises in the 80s and the 90s, an evolution opposite to the evolution for individuals with primary education.

Alternatively, one can simply use the log of immigrants as a measure of the immigration shock. Table 3 shows that the general picture of the immigration shock provided by this measure is similar to that provided by the immigrant share when we consider individuals with primary or secondary education. Instead, the number of immigrants with high-school or college education rises throughout the entire period, while the immigrant share for these groups follows a U-shape, as the educational level of natives was rising fast already before the 1980s (see Table 1).

Using the LFS and FQP data, we compute the average log monthly wage and convert it into 2007 euros using the CPI deflator from the French Statistical Institute (INSEE). Average log wages per experience and education level over the period are reported in Table 4. The picture

[9] For this education group, the starting date for the decline is staggered over time across experience groups, with the decline for the high-experienced coming later. Intuitively, this may simply reflect a large inflow of low-educated and low-experienced immigrants stopping in the mid 1970s and affecting in turn higher experience groups as they move up the experience ladder.

Table 2: Percent of Male Labor Force that is Foreign Born per Education/Experience cell

Education	Experience	1962	1968	1975	1982	1990	1999
Primary	1-5	10.7	7.1	8.5	9.6	8.3	6.5
School	6-10	12.5	14.1	14.6	10.6	12.0	11.8
	11-15	12.4	20.4	23.4	15.6	14.9	13.7
	16-20	11.2	16.9	27.5	21.1	16.1	16.5
	21-25	11.3	13.5	21.4	25.1	19.1	16.5
	26-30	13.4	12.1	16.0	22.8	21.7	16.6
	31-35	11.1	12.2	12.8	16.8	24.3	19.2
	36-40	9.9	12.3	11.8	13.0	18.7	21.6
Secondary	1-5	2.9	2.6	3.9	4.1	5.1	3.9
School	6-10	2.3	3.0	3.4	3.7	4.7	5.6
	11-15	2.1	3.4	4.0	3.8	5.0	6.0
	16-20	3.2	3.2	3.9	3.8	5.1	6.4
	21-25	4.5	3.7	3.8	3.8	5.1	6.4
	26-30	6.1	5.7	3.5	3.6	4.9	6.2
	31-35	3.8	6.2	4.9	3.1	4.5	6.0
	36-40	4.3	5.6	5.9	4.0	4.3	6.0
High	1-5	3.9	2.6	3.5	3.3	4.6	3.9
School	6-10	3.4	2.7	3.7	4.8	5.7	5.2
	11-15	3.5	3.2	4.1	4.8	6.9	8.6
	16-20	4.2	3.4	4.1	4.2	6.5	9.9
	21-25	4.2	3.9	3.4	4.3	4.8	9.3
	26-30	5.3	5.0	4.0	4.1	4.7	7.8
	31-35	5.6	5.6	4.8	3.8	4.5	6.4
	36-40	7.7	5.6	5.9	4.7	4.0	6.7
College	1-5	6.3	4.0	3.2	3.8	4.4	3.7
Graduates	6-10	5.2	5.0	5.2	5.5	7.4	6.2
	11-15	6.5	5.9	6.4	5.4	10.3	10.4
	16-20	6.2	5.4	6.7	6.4	8.0	11.9
	21-25	8.5	5.6	5.6	6.5	7.3	11.1
	26-30	7.4	6.8	5.2	5.8	8.3	8.4
	31-35	7.8	6.8	6.1	5.3	7.9	9.0
	36-40	8.6	7.9	7.4	5.5	7.1	10.3

Notes: For each census year, the Table reports the percentage of immigrants among workers with similar education level and labor market experience. *Sources:* Census of Population, 1962-1999

Table 3: Log Immigrants per Education/Experience cell

Education	Experience	1962	1968	1975	1982	1990	1999
Primary	1-5	10.40	10.51	10.47	10.39	9.73	9.00
School	6-10	11.46	11.57	11.60	11.14	10.85	10.12
	11-15	11.87	11.98	12.25	11.67	11.25	10.70
	16-20	11.88	12.04	12.23	12.14	11.48	11.05
	21-25	11.89	11.98	12.17	12.18	11.82	11.15
	26-30	11.67	11.89	12.07	12.11	12.03	11.31
	31-35	11.72	11.74	11.90	12.02	11.95	11.67
	36-40	11.72	11.52	11.81	11.86	11.88	11.81
Secondary	1-5	8.24	9.12	9.59	9.70	9.55	9.30
School	6-10	8.85	9.63	10.21	10.32	10.64	10.34
	11-15	8.72	9.54	10.19	10.30	10.77	10.77
	16-20	8.87	9.39	9.75	10.24	10.69	11.05
	21-25	9.03	9.32	9.62	9.73	10.61	11.04
	26-30	8.68	9.47	9.38	9.52	10.35	10.95
	31-35	8.33	9.22	9.42	9.23	9.84	10.84
	36-40	8.20	8.85	9.41	9.17	9.68	10.53
High	1-5	7.47	8.06	8.55	8.63	8.70	9.15
School	6-10	7.79	8.38	9.06	9.43	9.56	9.86
	11-15	7.88	8.39	8.86	9.44	9.81	10.05
	16-20	8.08	8.36	8.66	9.13	9.77	10.15
	21-25	7.88	8.46	8.37	8.81	9.47	10.07
	26-30	7.88	8.68	8.48	8.60	9.06	9.82
	31-35	7.90	8.22	8.61	8.45	8.81	9.53
	36-40	8.03	8.26	8.32	8.57	8.55	9.19
College	1-5	7.74	7.61	8.67	8.84	9.34	9.67
Graduates	6-10	8.14	8.41	9.41	9.70	10.21	10.48
	11-15	8.45	8.49	9.18	9.72	10.53	10.85
	16-20	8.35	8.41	8.94	9.40	10.31	10.86
	21-25	8.09	8.42	8.68	9.07	9.97	10.72
	26-30	8.17	8.10	8.55	8.72	9.58	10.43
	31-35	8.04	8.20	8.47	8.51	9.20	10.11
	36-40	7.99	8.22	8.27	8.45	8.96	9.78

Notes: For each census year, the Table reports the log of immigrants with similar education level and labor market experience. *Sources:* Census of Population, 1962-1999 for wages over time is quite simple and uniform across education/experience cells. Indeed, with few exceptions, wages rise during the period 1962-1976 and then decrease throughout the 1976-1999 period.

2 Econometric Model

2.1 Borjas model

The initial specification (Borjas, 2003) relates the labor market outcomes of natives to the immigrant share across education/experience groups:

$$y_{ijt} = \theta p_{ijt} + \psi_{FE} + \varphi_{ijt} \tag{2}$$

where y_{ijt} is a labor market outcome at period t for natives with education i and experience j, p_{ijt} is the immigrant share, and ψ_{FE} is a set of education, time, and experience fixed effects s with their corresponding interactions i.e. $\psi_{FE} = s_i + s_j + s_t + (s_i \times s_j) + (s_i \times s_t) + (s_j \times s_t)$. A problem might arise if the immigrants with given education/experience levels are attracted by the labor market outcomes of specific cohorts of natives, defined here as a group of workers entering the labor market at a specific time and with a specific educational level.[10] Indeed, as (2) does not control for cohort effects, our results could be biased if the error term includes unobserved cohort effects correlated with the immigrant share. Figure 1 represents the evolution over time of the immigrant share for each cohort as defined in Table 5.[11] The variation in the immigrant share over time is generally important for workers with primary education, particularly in cohorts 1, 8, and 10. For the other educational groups, the variation is smaller but non-negligible. Still, most of the differences in the immigrant shock arise (i) across educational groups within given cohorts, or (ii) across cohorts within given educational groups.

[10] As recognized in the literature, cohort effects might influence labor market outcomes, as shown for instance by Card and Lemieux (2001) who argues that cross cohort differences in size and education can explain recent trends in wage inequality in the U.S. Alternative explanations for cohorts effects have been proposed by Beaudry and DiNardo (1991) and Gibbons and Waldman (2004). As first emphasized by Deaton (1985), a cohort, defined as a group with fixed membership, can be tracked over time using repeated cross-section.

[11] Given that censuses in France have not been conducted in regular intervals of 5 or 10 years, an alternative would be to change over time the age brackets definition of the experience intervals.

Table 4: Log Monthly Wage of Full Time Male Native Workers Per Education/Experience

Education	Years of Experience	1962	1969	1976	1982	1990	1999
Primary	1-5	6.132	6.593	6.351	6.825	6.586	6.445
Education	6-10	6.480	6.875	7.061	6.981	6.923	6.927
	11-15	6.627	7.009	7.207	7.089	7.021	7.026
	16-20	6.683	7.027	7.299	7.179	7.109	7.112
	21-25	6.668	7.113	7.296	7.237	7.185	7.154
	26-30	6.653	7.109	7.303	7.248	7.256	7.193
	31-35	6.646	7.131	7.285	7.232	7.264	7.28
	36-40	6.626	7.115	7.242	7.238	7.234	7.348
Secondary	1-5	6.417	6.855	6.605	6.917	6.842	6.667
Education	6-10	6.683	7.084	7.219	7.093	7.023	7.010
	11-15	6.879	7.234	7.388	7.246	7.165	7.133
	16-20	6.984	7.354	7.521	7.374	7.256	7.236
	21-25	7.057	7.438	7.559	7.444	7.354	7.311
	26-30	7.082	7.537	7.566	7.489	7.443	7.371
	31-35	7.071	7.459	7.566	7.477	7.463	7.438
	36-40	7.223	7.575	7.666	7.520	7.455	7.490
High	1-5	6.739	7.184	7.033	7.100	7.089	6.951
School	6-10	7.074	7.432	7.521	7.350	7.233	7.118
	11-15	7.473	7.637	7.784	7.545	7.421	7.358
	16-20	7.600	7.714	7.800	7.698	7.596	7.539
	21-25	7.662	7.874	7.965	7.828	7.697	7.630
	26-30	7.458	7.811	7.961	7.857	7.765	7.640
	31-35	7.539	7.854	8.047	7.813	7.784	7.775
	36-40	7.384	7.836	7.99	7.915	7.808	7.885
College	1-5	7.176	7.764	7.506	7.423	7.393	7.304
Graduates	6-10	7.798	8.074	7.960	7.700	7.650	7.510
	11-15	8.099	8.244	8.173	7.941	7.802	7.753
	16-20	7.911	8.368	8.223	8.149	7.945	7.934
	21-25	7.997	8.486	8.499	8.283	8.044	7.982
	26-30	8.317	8.485	8.426	8.314	8.144	8.107
	31-35	8.052	8.492	8.529	8.271	8.164	8.190
	36-40	8.274	8.609	8.679	8.220	8.181	8.288

Notes: The table provides the average log monthly wage of native men, working full time, per group of education and experience. See text for details. The population excludes self-employed and civil servants. Wages are deflated in 2007 Euros using the CPI computed by the INSEE. *Sources:* FQP 1964, 1970, 1977 and LFS 1982, 1990, 1999.

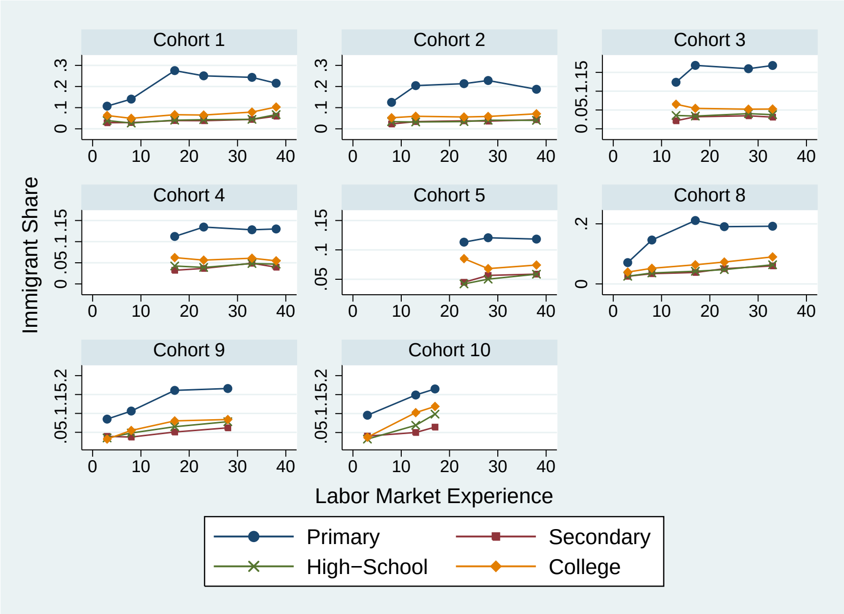

Figure 1: Fluctuations of the immigrant share by educational group in specific cohorts
Sources and notes: Each panel represents the evolution over time of the immigrant share for given cohorts of workers for each educational level. The definition of the cohorts is given in Table 5. The sample includes men with experience between 1-40. Data from censuses 1962-1999.

Finally, despite the large number of fixed effects in the OLS regressions, estimates of θ are biased if the immigrant share depends on the *particular* outcomes of a cell. Assuming there is no autocorrelated cohort effect in the error term, a plausible instrument for p_{ijt} is the immigrant share of the same cohort of workers in the preceding census $p_{i,(j,t)_{-1}}$, i.e. i-level educated workers with $j-k$ to $j-k+5$ years of experience in census year $t-k$.[12] Indeed, given that most immigrants stay in the host country independently of changes in labor market conditions,[13] $p_{i,(j,t)_{-1}}$ is likely to be correlated with the contemporary immigrant share p_{ijt} and uncorrelated to contemporary outcomes in the cell conditional on the inclusion of other covariates.

2.2 Log of natives and log of immigrants

Clearly, if the number of natives within given education/experience cells is stable over time, changes in the immigrant share will essentially capture variations in the number of migrants

[12]For instance, the immigrant share in 1968 for primary education workers with 20-25 years of experience is instrumented by the immigrant share in 1962 for primary education workers with 15-20 years of experience

[13]For example, Schor (1996) shows that subsidies to the return of immigrants to their country of origin during economic downturns were never successful in the French case.

Table 5: Definition of Cohorts

	Experience groups in the indicated census					
Cohort Number	1962	1968	1975	1982	1990	1999
1	1-5	6-10	16-20	21-25	30-35	36-40
2	6-10	11-15	21-25	26-30	36-40	
3	11-15	16-20	26-30	31-35		
4	16-20	21-25	31-35	36-40		
5	21-25	26-30	36-40			
6	26-30	31-35				
7	31-35	36-40				
8		1-5	6-10	16-20	21-25	31-35
9			1-5	6-10	16-20	
10				1-5	11-15	16-20
11					1-5	11-15

over time in these cells. However, if the number of natives is not stable, using the immigrant share constrains the effect of an increase in the number of immigrants and a decrease in the number of natives to be the same. Given that France experienced a large increase in general high-school graduation rates in the period under consideration (see Table 1),[14] a specification where both the number of natives and the number of immigrants are included as regressors may be preferable. In addition, if immigrants are not perfect substitutes with natives, immigrants might still have an impact on the outcomes of natives even if their share within the cell is fairly constant over time. For these reasons, as an alternative, we estimate a model including both the log of number of natives and the log of the number of mmigrants as regressors:[15]

$$y_{ijt} = \theta_M \log M_{ijt} + \theta_N \log N_{ijt} + \psi_{FE} + \varphi_{ijt}. \tag{3}$$

The previous model is very close to the one proposed by Borjas (2003, p. 1361, eq. 14) to estimate the elasticity of substitution between experience groups except that it allows for a separate effect of the log of natives and the log of immigrants on the outcomes of the cell.

[14]Instead, in the U.S. the educational attainment of the population remained fairly constant over this period, see Goldin and Katz (2008).

[15]This alternative is not used by Borjas (2003) because in his data 15.3% of the education/experience cells by state of residence have no immigrants. Instead, with our very large sample extracts, only 2.5% of our education/experience cells at the regional level have no immigrants.

2.3 Including occupations

Models (2) and (3) directly estimate the relationship between immigration and wages within education/experience cells. However, immigrants may simultaneously affect wages within occupations and the allocation of workers across occupations. Formally, if immigrants have an impact on the occupational distribution of natives, then the changes in the wage of workers in a particular (i, j, t) cell following the presence of M_{ijt} immigrants in that cell can be decomposed into the effect of immigration on wages and the effect of immigration on occupations k:

$$\frac{\partial \log w_{ijt}}{\partial M_{ijt}} = \sum_k \frac{\partial s^k_{ijt}}{\partial M_{ijt}} \log w^k_{ijt} + \sum_k s^k_{ijt} \frac{\partial \log w^k_{ijt}}{\partial M_{ijt}} \tag{4}$$

where $\log w^k_{ijt}$ is the average log wage in cell (i, j, t, k) and s^k_{ijt} is the share of workers from cell (i, j, t) working in occupation k. In particular, if natives move to better paid occupations in response to immigrants flows, it is thus theoretically possible that immigration increases average wages within cells (i, j, t) even if it decreases wages within some or all occupations.

Recently, some papers have highlighted a link between immigrant flows and natives' occupations. In particular, Peri and Sparber (2009) provides evidence across US states that low-skilled natives respond to immigration by specializing in language intensive tasks for which they have a comparative advantage and which are better remunerated than manual-physical tasks, while Card and Lewis (2007) find that low skill immigrant inflows change the skill intensity within industries without affecting relative wages across US states. Here, we try to disentangle the effect of immigration on wages and occupations by directly estimating an occupational premium, following the well established "industry premium" literature initiated by Krueger and Summers (1987, 1988).[16]

Formally, we decompose average wages within occupations k in a cell i, j by an invariant across occupations part and an invariant across cells part, i.e. $\log w^k_{ijt} = a_{ijt} + \log w^k_t + \epsilon_{ijtk}$. The first term a_{ijt} corresponds to the cohort-specific component of wages, which might depends on the supply of education and experience across cohorts (Card and Lemieux, 2001) and

[16] In contrast with the tasks-content index in Peri and Sparber (2009), our estimated occupational premium is year-specific and thus can vary over time, which is a nice feature if immigration alters the educational composition of workers within industries as emphasized by Card and Lewis (2007).

is constant across occupations by assumption. The second term $\log w_t^k$ is the wage premium for workers in occupation k at time t invariant across education/experience cells, and ϵ_{ijtk} is an error term assumed to be i.i.d. with a zero average. Adding up across occupations, the average log wages within education/experience cells can be rewritten as:

$$\log w_{ijt} = a_{ijt} + \sum_k s_{ijt}^k \log w_t^k + u_{ijt} \tag{5}$$

where u_{ijt} is an error term.

To estimate $\log w_t^k$, we regress individual wage data from labor force surveys for each year on education and experience fixed effects and interactions which absorb the effect of differences in workers characteristics across occupations. Then, the occupational premia are computed taking blue collar agricultural workers as the reference occupation. However, the relative wages may vary over time, which would affect the *level* of occupational premia across years. Thus, we standardize average occupational premia within cells with respect to the average premium in the workforce each year. In other words, denoting by $Occup_t = \sum_{k,i,j} s_{ijt}^k \log w_t^k$ the average occupational premium in year t for the entire workforce, we compute for each cell $Occup_{ijt} = \sum_k s_{ijt}^k \log w_t^k - Occup_t$ i.e. the average occupational premium within the cell normalized with respect to the average year t premium.[17]

An occupation is here defined as a professional status (white collar worker, technician, or blue-collar worker) within a particular industry at various levels of aggregation (from 10 to 100 industries), implying that we have between 30 and 300 occupations.[18] Interacting professional status with industry allows us to identify the impact of immigration on natives occupations both within and across industries after an immigration shock.

Figure 2 presents the average wage within education/experience cell against the occupational premium computed using 300 occupations. Both variables are strongly and positively

[17] Alternatively, note that our occupational premium can be interpreted as the average rent of workers within an education/experience cell, as workers in high wages industries are likely to earn substantial rents (see Krueger and Summers, 1988, and Katz and Summers, 1989).

[18] Professional status corresponds to the *catégories socio-professionnelles* (*cadre*, *technicien*, and *ouvrier*) established by INSEE. Industries are defined using the NAP industry classification. As industry codes are not reported at the four digit level in the 1962 Census, the analysis only includes data from the 1968 to 1999 censuses. The industry classification system used across censuses has been harmonized to keep the definition of occupations unaffected by changes in classification systems over time in the data. Appendix 1 provides details on crosswalk tables for industry classifications.

Figure 2: Average Log Wages and Occupational Premium

Notes: The figure plots the average log wage of workers in education/experience cells against the estimated occupational premium. See text for details. *Sources*: FQP, LFS, and Census data 1962-1999.

correlated, with a 0.93 correlation coefficient over the whole sample,[19] which suggests that the variation in average wages across education/experience cells is strongly related to differences in the occupational distribution of the individuals within the cells.[20] After including the occupational premium $Occup_{ijt}$, our model becomes:

$$\log w_{ijt} = \theta_1 \log N_{ijt} + \theta_2 \log M_{ijt} + \gamma Occup_{ijt} + \psi_{FE} + \varphi_{ijt}. \quad (6)$$

The occupational premium will absorb the differences in wages across cells coming from differences in the occupational distribution of workers across occupations. Then, we can also test whether immigrants influence the average "quality" of natives' occupations within education/experience cells, i.e. whether $Occup_{ijt}$ is itself a function of $\log M_{ijt}$. To test that hypoth-

[19]The correlation is also high for each census year taken separately.

[20]Our assumption of an invariant across-groups wage premium for occupations is consistent with French data, as it is for U.S. data (see Krueger and Summers, 1987, 1988). Indeed, the occupational premia estimated separately for given education/experience levels happen to be highly correlated. For example, the correlation between the occupational premia for individuals with 1-20 years of experience and the premia for workers with 20-40 years of experience is 0.96 (resp. 0.97) when we consider 63 (resp. 30) occupations. Similarly, the correlation coefficient between estimates using only either low educated (primary and secondary) workers or highly educated (high-school and college) workers is 0.88 with 63 occupations (0.91 with 30). These correlations remain strong for industry classifications at different levels of aggregation, which confirms that occupational premia are relatively unrelated to individual characteristics.

esis, we estimate:

$$Occup_{ijt} = \beta_1 \log N_{ijt} + \beta_2 \log M_{ijt} + \psi_{FE} + u_{ijt}. \tag{7}$$

Finally, we estimate models to determine whether immigrants and natives within given education/experience cells specialize in the same occupations. Following Peri and Sparber (2009), we look at the relation between the log of natives and immigrants and the *relative* occupational distribution of immigrants versus natives. We first compute the occupational premium of immigrants across cells $Occup_{ijt}^{immig} = \sum_k s_{ijt}^{k,immig} \log w_t^k - Occup_t$ where $s_{ijt}^{k,immig}$ is the share of immigrants in cell (i, j, t) working in industry k. The relative occupational differential between natives and immigrants within cells is then simply $Relat_{ijt} = Occup_{ijt} - Occup_{ijt}^{immig}$.[21] If immigrants and natives specialize in similar occupations within education/experience cells, one should not expect a different impact of the number of natives and the number of immigrants on the relative occupational premium of natives. This hypothesis can be tested by estimating the following specification:

$$Relat_{ijt} = \delta_1 \log N_{ijt} + \delta_2 \log M_{ijt} + FE + \varphi_{ijt}. \tag{8}$$

Similarly, we estimate the relationship between the number of natives and immigrants and the average occupational premium of immigrants across cells using the following regression:

$$Occup_{ijt}^{immig} = \eta_1 \log N_{ijt} + \eta_2 \log M_{ijt} + FE + \upsilon_{ijt}. \tag{9}$$

If large immigrant shares come from the immigrants being attracted by better-paid jobs available in the cell for both immigrants and natives, we expect to observe a positive correlation between the occupational premium of immigrants and the log of immigrants in the cell.

As we do not need wages to compute the relative occupational premium, we can also study how this premium depends on the number of natives and immigrants when a geographical dimension is added to the analysis. In addition to providing a robustness check, this enables us

[21] We use the difference instead of the ratio because $Occup$ represents differences in log wages, which implies that $Relat_{ijt} = \sum_k \left(s_{ijt}^k - s_{ijt}^{k,immig} \right) \log w_t^k$.

to use the proportion of co-nationals in the region as an instrument, as e.g. in Altonji and Card (1991) and Cortes (2008). Specifically, the instrument is given for each year t and region C by

$$\sum_{C}\left(\frac{Immigrants_{CR,Ref}}{Immigrants_{C,Ref}}\right) * Immigrants_{C,ijt}, \tag{10}$$

where $\frac{Immigrants_{CR,Ref}}{Immigrants_{C,Ref}}$ is the proportion in year Ref of country-C immigrants living in region R, while $Immigrants_{C,ijt}$ is the total number of immigrants from country C with education i and experience j in France in year t. Given our large sample size, we distinguish groups of immigrants by using the maximum number of nationalities available, namely the 54 different countries of birth which are always reported separately across censuses. [22] Using the variation in the occupational distribution of natives and immigrants across regions, we then compute for each education/experience cell the occupational premium of immigrants and natives at the regional level, together with the relative occupational premium.[23]

There are several potential econometric problems to the estimations of the model (6). Even if one assumes the number of natives (N) and the number of immigrants (M) to be exogenous in (6) and (7), φ and u might be correlated or equivalently, the occupational premium $Occup$ might be correlated with φ, leading the OLS estimates of (6) to be inconsistent. We use 2SLS with various instruments for occupations to deal with this issue. We first construct two instruments using a shift-share model following Bartik (1991). We use the national trends in occupations across education/experience cells to predict the change in the occupational premium over time within cells. By construction, this evolution is common to all groups and thus unrelated with the variations over time of the immigrant share across education/experience cells. More specifically, denoting by N_t^k the number of workers in occupation k at year t, we predict the number of workers in occupation k within cell (i, j, t) by $\hat{N}_{ijt}^k = N_{i,j-l,t-l}^k(1 + g_{t,k})$ where $g_{t,k} = \frac{N_t^k}{N_{t-l}^k} - 1$ is the growth rate of employment in sector k between census t and year $t - l$

[22]We use two versions of this instrument. The first version uses 1968 as the reference year for all censuses, while our second version uses the lagged census year as a reference year. The two versions are likely to be quite different given that the stock of immigrants in 1968 is concentrated in regions with large cities and comes mainly from Europe and the Maghreb, while post-1970s immigration comes also from Asia and Sub-Saharan Africa and is more spread across regions. Therefore, in some sense, the first version of the instrument uses traditional long run immigrant flows while the second instrument is related with more recent immigrant waves.

[23]This implicitly assumes a constant occupational premium across regions. We have found no evidence that occupational premia would vary across regions, as in the literature on industry premiums mentioned above.

for the whole labor force. Then, we use the predicted number of workers across occupations to compute a counterfactual occupational premium of the cell assuming employment in each occupation follows the national trend, i.e., $\hat{Occup}_{ijt} = \sum_k \hat{s}^k_{ijt} \log w^k_t$ where $\hat{s}^k_{ijt} = \frac{\hat{N}^k_{ijt}}{\hat{N}_{ijt}}$ and $\hat{N}_{ijt} = \sum_k \hat{N}^k_{ijt}$. We also construct a second counterfactual shift-share premium using only industrial affiliations of workers within education/experience cells. This variable measures the pure industry wage differential, i.e. does not take into account that workers within a given industry will have different wages depending on their professional status.

Finally, we also use an instrument which exploits cohort effects across occupations. Indeed, existing evidence shows that the distribution of workers across industries depends on labor demand across industries at the time of entry of the cohort in the labor force (Autor and Dorn, 2009) and it persists over time since industry specific human capital makes it costly for cohort members to change industry (Neal, 1995). Then, the successive occupational distributions of cohorts are correlated over time, and this does not depend on variations in immigrant flows over time but rather on labor market opportunities across industries at the time of entry in the labor force. So a simple instrument for $Occup_{ijt}$ is to use the lag of the occupational premium across cohorts $Occup_{i,(j,t)_{-1}}$, with cohorts still being defined by Table 5.

3 Results

This section presents the main empirical findings of the paper. Section 3.1 presents the estimates of the Borjas (2003) specification, section 3.2 uses a specification including the log of natives and the log of immigrants, and Section 3.3 presents the estimates when occupations are explicitly taken account for in the analysis.

3.1 Borjas model

Table 6 presents estimates of the Borjas (2003) model in (2). The upper panel presents estimates using OLS or WLS. In the baseline case (row 1), and in contrast with Borjas (2003), the immigrant share is found to be positively and significantly correlated with the average log monthly wage (column 1), the employment to population ratio (column 2) and the employment

Table 6: Impact of Immigrant Share per Education/Experience Cells

Specification	Av. Log Monthly wage	Employment Population	Employment Labor Force	Cragg-Donald Wald F-stat	N
		A. WLS/OLS			
1. Basic Estimates	0.403**	0.380***	0.312***		192
	(0.186)	(0.112)	(0.071)		
2. Unweighted Regression	0.277	0.492**	0.364***		192
	(0.286)	(0.210)	(0.117)		
3. Experience	0.278	0.194***	0.213***		96
between 11 and 30	(0.210)	(0.042)	(0.042)		
4. Only Primary	0.480**	0.294***	0.288***		96
and Secondary Education	(0.205)	(0.094)	(0.085)		
5. Estimates without	0.301	0.361***	0.261***		
1-10 years exp.	(0.189)	(0.112)	(0.055)		144
		B. 2SLS			
6. Basic Estimates	0.338***	0.364***	0.275***	180.8	116
	(0.128)	(0.063)	(0.034)		
7. Without weights	0.272**	0.542***	0.312***	179.4	116
	(0.139)	(0.152)	(0.048)		
8. Experience	0.407**	0.267***	0.277***	25.9	64
between 11 and 30	(0.197)	(0.061)	(0.070)		
9. Only Primary	0.432***	0.286***	0.252***	64.4	58
and Secondary Education	(0.139)	(0.036)	(0.030)		
10. $p_{i,(j,t)_{-2}}$ as IV	0.393***	0.267***	0.154***	80.8	72
	(0.153)	(0.071)	(0.028)		
11. $p_{i,(j,t)_{-3}}$ as IV	0.259*	0.352***	0.162***	30.9	40
	(0.136)	(0.105)	(0.012)		

Notes: The table reports the coefficient of the immigrant share from regressions with the indicated dependent variables using observations from the period 1962-1999. For rows 6 to 11, the model is estimated using 2SLS taking $p_{i,(j,t)_{-1}}$ as an instrument. The fourth column reports the Cragg-Donald Statistic for weak instrument. The last column reports the number of observations. The critical value at 10% is 16.38 (Stock and Yogo, 2005). Robust heteroscedastic standard errors reported in parenthesis are adjusted for clustering within education/experience cells. Controls (fixed effects) are added for education, experience, year, and for interactions between education and experience, year and experience, education and year. When the dependent variable is the employment to population or the employment to labor force rate, weights are the number of natives per cell divided by the total number of natives in the census year. When the dependent variable is the average log wages, weights are the number of observations per cell used to compute the average wage with the LFS or FQP divided by the total number of observations used to compute average wages per year. *, ** and *** denotes significant at respectively 10%, 5% and 1% level. *Sources:* Census of Population 1962-1999, FQP 1964, 1970, 1977 and LFS 1982, 1990, 1999.

to labor force ratio (column 3). Quantitatively, the estimated impact of is quite large: a 10% increase in the immigration share is estimated to raise native's wages by 3.4%, the employment/population ratio by 3.2%, and the employment/labor force ratio by 2.7%.[24]

A first concern for the validity of these initial estimates is that changes in participation rates and wages across demographic groups over this period might be spuriously correlated with variations of the immigrant share. Although France and the U.S. experienced similar employment-population ratios during the 60s, the employment population ratio in France fell dramatically after that period both for both young workers (under 25) and old workers (above 55). Even if our model controls for interactions between experience and year which should absorb the effect of this change across education groups over time, our results may potentially reflect these changes if immigration was lower for some cells within education groups. As a check of the robustness of our findings, Row 3 eliminates from the sample the cells of less than 11 years of experience and more than 30 years of experience. In that case, the estimated effects of immigration on log wages and employment rates remain positive, although non significant for wages.

A second issue is that the impact of immigration could differ across educational groups in which case our estimates may reflect the simultaneous increase in immigration and wages for the most educated groups. However, the estimates in Row 4 for low educational levels (primary or secondary education only) still display a positive and significant correlation between immigration and wages, and a positive (although of lower magnitude) correlation with employment rates.[25]

Row 5 shows that the coefficients remain similar when we exclude from the analysis the individuals with less than 10 years of experience, for which the prevalence of the minimum wage is very important, especially after 1975.[26] The minimum wage is thus unlikely to be the

[24] When the endogenous variable y_{ijt} represents the wage, the parameter θ can be interpreted as an elasticity giving the percentage change in wages associated with a percentage change in labor supply. As in Borjas (2003), we define the "wage elasticity" as $\partial \log w/\partial m = \theta/(1+m)^2$ Over the period, the mean value of the relative number of immigrants (m) is about 9%. The wage elasticity evaluated at the mean value can therefore be obtained by multiplying θ by 0.85.

[25] The estimated impact of immigration for the individuals with more than secondary education only (not reported) is negative but never significantly different from zero

[26] The proportion of natives paid at the minimum wage plus 5% peaks at 87.3% in 1999 for the individuals with primary education and experience level 1-5, increases rapidly over time, and is generally non negligible among the least educated for all experience levels and the least experienced for the all education levels. Instead, the share is

main factor behind the positive correlation between immigration and natives' labor market outcomes.

To account for the potential endogeneity of the immigrant share, the lower panel of the table reports 2SLS estimates where the immigrant share is instrumented by the past immigrant share at the cohort level. The last column presents the Cragg-Donald test statistics. For all regressions, the instrument proves to be strong compared to the critical 10% value of 16.38 reported in Stock and Yogo (2005). This also suggests, as discussed before, that the immigrant share is strongly correlated over time at the cohort level. Table 6 shows that the IV estimates are not very different from the OLS estimates, implying that the potential endogeneity of the immigrant share does not seem to affect the estimates to a large extent.

In case the distance between two consecutive censuses would not be sufficient to purge the potential endogeneity of the immigrant share, which may be particularly the case if the error terms are serially correlated at the cohort level, rows 10 and 11 use as instruments the immigrant share in increasingly distant censuses, with the estimates remaining qualitatively unchanged.

Appendix 2 shows that the positive correlation between the immigration share and the employment outcomes of natives still holds when we define education/experience cells at the *département* (county) level. As in Borjas (2003), however, the value of the estimated coefficients is attenuated.

3.2 Log of Natives and log of Immigrants

Table 7 reports the estimates from regressions where the log of natives and the log of immigrants are included as regressors. Across specifications, the coefficient of the log of natives is most of the times negative, while the coefficient of the log of immigrants is generally positive, which could be interpreted as evidence of imperfect substitutability between immigrants and natives within education/experience cells. Quantitatively, the results show that a 10% increase in the number of immigrants increases wages by between 0.2 and 0.4 % which is much smaller

systematically below 5% for individuals with at least high school education and more than ten years of experience. A table presenting the share of workers paid at the minimum wage across education/experience cells is available upon request.

Table 7: Impact of the Log of Immigrants and the Log of Natives per Education/Experience Cells

	Dependent variable				
Specification	Av. Log Monthly wage	Log Employment Population	Log Employment Labor Force	Cragg-Donald Wald F-Stat	N
		A. WLS/OLS			
		1. Basic Estimates			
Log natives	-0.071*	0.014	-0.010		192
	(0.042)	(0.028)	(0.016)		
Log immigrants	0.032	0.078***	0.050***		
	(0.024)	(0.021)	(0.009)		
		2. Unweighted Regression			
Log natives	-0.024	0.043	0.008		192
	(0.052)	(0.031)	(0.015)		
Log immigrants	0.012	0.093***	0.054***		
	(0.035)	(0.032)	(0.015)		
		B. 2SLS			
		4. Basic Estimates			
Log natives	-0.092***	0.042	-0.021**	93.7	116
	(0.024)	(0.034)	(0.011)	[16.4]	
Log immigrants	0.031*	0.087***	0.043***		
	(0.017)	(0.019)	(0.006)		
		5. Unweighted Regression			
Log natives	-0.091***	0.061*	-0.016**	103.6	116
	(0.032)	(0.034)	(0.007)	[16.4]	
Log immigrants	0.035*	0.110***	0.049***		
	(0.021)	(0.022)	(0.006)		

Notes: The table reports the coefficients of the log of natives and immigrants from regressions with the indicated dependent variables using observations from the period 1962-1999. Controls (fixed effects) are added for education, experience, year, and for interactions between education and experience, year and experience, education and year. Robust heteroscedastic standard errors reported in parenthesis are adjusted for clustering within education/experience cells. The fourth column reports the Cragg-Donald Statistic for weak instrument. The critical value at 10% is 16.38 (Stock and Yogo, 2005). The last column indicates the number of observations. When the dependent variable is the log employment to population or the log employment to labor force rate, weights are the number of natives per cell divided by the total number of natives in the census year. When the dependent variable is the average log wage, weights are the number of observations per cell used to compute the average wage with the LFS or FQP divided by the total number of observations used to compute average wages per year. *, ** and *** denotes significant at respectively 10%, 5% and 1% level. *Sources:* Census of Population 1962-1999, FQP 1964, 1970, 1977 and LFS 1982, 1990, 1999.

Table 8: Correlation among the number of natives, the number of immigrants, and the immigrant share across education/experience/year cells

Correlation	All workers	College	High-School	Secondary	Primary
$\sharp$ Natives - $\sharp$ Immigrants	0.77	0.886	0.83	0.93	0.645
$\sharp$ Immigrants -Immigrant Share	0.88	0.64	0.74	0.58	0.71
$\sharp$ Natives -Immigrant Share	0.458	0.29	0.3	0.3	-0.03

Source: Census of Population, 1962-1999.

than the 3 % impact found in Table 6 when immigration is measured by the immigrant share. This dramatic reduction in the size of the effect is likely to be related to the variation in the immigrant share being smaller than the variation in the log of immigrants. Indeed, Table 8 shows that the number of immigrants and the number of natives are highly positively correlated across education/experience/time cells. As a result, the immigrant share is actually positively correlated to the number of natives (except for the individuals with primary education) despite the fact that the number of natives enters the immigrant share in the denominator. The strong positive correlation between the number of immigrants and the number of natives also explains why the coefficient of variation of the immigrant share across education/experience/time cells (0.66) is smaller than the coefficients of variation of the number of natives and the number of immigrants (respectively 0.82 and 1.33).

To understand the positive impact of immigration on wages and the asymmetry in the effects of the number of natives and the number of immigrants, the next section studies whether occupations play a role in explaining differences in outcomes across cells (3.3.1) and how the occupational premia of natives and immigrants depend on the size of these two groups (3.3.2).

3.3 Occupations

3.3.1 Natives wages, immigration, and occupations

In principle, immigrants could have a positive effect on the wages of natives by displacing them to better paid occupations. To test this, Table 9 reports the estimates of model (6), i.e.[27]

$$\log w_{ijt} = \theta_1 \log N_{ijt} + \theta_2 \log M_{ijt} + \gamma Occup_{ijt} + \psi_{FE} + \varphi_{ijt}$$

[27] We show here only results for the case of 100 industries interacted with three professional status. Results using 41, 21 and 10 industries are broadly similar and available upon request.

Table 9: Immigration and Occupation

	Dependent Variable: Average log Monthly Wage			
Method of Estimation	WLS	2SLS		
Log natives	-0.038	-0.023	-0.094**	-0.062**
	(0.036)	(0.043)	(0.045)	(0.024)
Log immigrants	0.028	0.029**	0.079**	0.026**
	(0.020)	(0.014)	(0.023)	(0.013)
Occupational premium	0.742*	0.848**	-0.939	0.335
Natives	(0.410)	(0.334)	(0.640)	(0.294)
Test of over-identifying	NA	0.01	3.05	6.08
restrictions (p-value)		(0.91)	(0.21)	(0.02)
Cragg-Donald		49.3	15.56	31.7
Number of observations	128	132	88	116
Excluded Instruments				
Lagged Occup. Premium		N	Y	N
Predicted Occupation Premium		Y	Y	Y
Predicted Industry Premium		Y	Y	Y

Notes: The table reports the coefficients from regressions using observations from the period 1968-1999. Controls (fixed effects) are added for education, experience, year, and for interactions between education and experience, year and experience, education and year. Robust heteroscedastic standard errors reported in parenthesis are adjusted for clustering within education/experience cells. The regressions are weighted using the number of immigrants in the cell. The regressions in columns 2 to 4 use the predicted occupational and industry premium as excluded instrument. The regression in column 3 also uses the lagged and predicted occupational premium as excluded instrument. The regression in column 4 uses the lagged log immigrant at the cohort level as an additional excluded instrument for the log of immigrants. *, ** and *** denotes significant at respectively 10%, 5% and 1% level. *Sources:* Census of Population 1968-1999, FQP 1964, 1970, 1977 and LFS 1982, 1990, 1999.

The WLS estimates in column 1 report a positive correlation between the occupational premium of natives and their wages, as suggested by Figure 2, while the log of immigrants is still positively (but not always significantly) correlated with wages. OLS regressions results suggest that most of the correlation between average wages and outcomes are related with differences in distribution across occupations. However, these estimates are inconsistent if immigrants influence the occupational choice of natives and the unobserved factors influencing occupational premia and wages within education/experience cells are correlated. To deal with this issue, column 2 reports 2SLS estimates using two shift-share counterfactual premia, column 3 includes the lagged occupational premium as an additional instrument, and column 4 instruments the log of immigrants in the cell with the lags of this variable at the cohort level.

Interestingly, after instrumentation, the coefficient of the log of immigrants becomes significant. Compared with OLS estimates, 2SLS results indicate a larger and significant effect of both the log of immigrant and of the log of natives or the log of the total number of workers in the cell. The point estimates of the occupational premium are much lower and not significant. Quantitatively, 2SLS regressions predict that an increase of 10% in the number of immigrants in the cell increases natives average wages by between 0.3 to 0.8%. As a further robustness check for our result, column 4 reports estimates where the log of immigrants in the cell is instrumented using the lags of this variable at the cohort level, as in the previous section. The results from column 4 lead to a point estimate that is similar to the corresponding estimates in column 2.

Overall, these results suggest that naive estimates of the impact of immigration conditioning for occupations may be biased because immigrants influence the occupational distribution of natives. Once this source of bias has been taken into account, we find a positive impact of the log of immigrants on the wages of natives. In the next section, we explicitly study the relation between immigration and the occupational premium of natives and immigrants.

3.3.2 Occupational Premia and Immigration

National Level Table 10 reports the estimates of the regressions explaining the occupational premium of natives (Panel A), immigrants (Panel B) and the relative occupational premium of natives (Panel C) as a function of the log of natives and the log of immigrants (i.e. respectively models 10 ,7, and 8). Consistent with the idea that natives compete mainly with natives, the occupational premium of natives is found to be negatively correlated with the log of natives and positively correlated with the log of immigrants. In addition, the estimated elasticities show that the occupational premium of natives is much more sensitive to the number of natives than to the number of immigrants.[28]

The positive correlation between the occupational premium of natives and the log of immigrants in Panel A could result from the immigrants self-selecting into the occupations where natives are better paid. This could be clearly the case if the best paid occupations for immigrants are the same as the best paid occupations for natives. However, panel B reports a

[28] We estimated the main model in Table 10 using alternative definitions of occupations and obtained similar results

Table 10: Occupational Premia

Dependent Variable:		
A. Occupational Premium of Natives		
Log natives	-0.057***	-0.053***
	(0.010)	(0.007)
Log immigrants	0.012**	0.011**
	(0.004)	(0.004)
B. Occupational Premium of Immigrants		
Log natives	-0.015	-0.029***
	(0.010)	(0.007)
Log immigrants	-0.021***	-0.027***
	(0.005)	(0.003)
C. Relative Occupational Premium		
Log natives	-0.050***	-0.024***
	(0.008)	(0.007)
Log immigrants	0.026***	0.037***
	(0.006)	(0.003)
Immigrant Share Instrumented	No	Yes
N	160	116

Notes: The three panels of the table report the coefficient of regressions relating the occupational premium of natives (Panel A), immigrants (Panel B), and the relative occupational premium of natives (Panel C) with the log of immigrants and log of natives across education/experience cells. Each model includes fixed effects and two-ways interactions between year, experience, and education. Occupational premia are calculated using the interaction between 3 professional status and 100 industries. All regressions are weighted using the number of immigrants in an education/experience cell. Robust heteroscedastic standard errors reported in parenthesis are adjusted for clustering within education/experience cells. *, ** and *** denotes significant at respectively 10%, 5% and 1% level.

negative and significant correlation between the occupational premium of immigrants and the log of immigrants, which is inconsistent with the self-selection hypothesis. Instead, these estimates indicate that immigrants within education/experience cells tend to compete with each other but not with natives. In addition, panel C shows that the relative occupational premium of natives is positively correlated with the log of immigrants within the cell. These results strongly suggest that natives and immigrants in given education/experience cells have different patterns of specialization across occupations.

As natives in cells with many immigrants tend to work in occupations yielding higher wage premia than natives in cells with a smaller number of immigrants, these results indicate that immigration may influence natives' labor market outcomes by triggering their reallocation towards better paid occupations within education/experience cells. In particular, if immigration helped natives climb the occupational ladder, the arrival of immigrants to a given education/experience cell would enfranchise natives in the cell from working in low-paid occupations and enable them to move to better-paid occupations. As a result, there would be a negative (respectively, positive) correlation between the proportion of immigrants in a given in education/experience cell and the proportion of natives in the cell enrolled in the worst-paid (respectively, best paid) occupations. Table 11 provides evidence pointing in this direction by regressing the share of workers in each occupational category on the share of immigrants. These regressions are performed separately across groups of education and include controls for cohort effects to account for the fact the probability of accessing a specific group of occupations with a given diploma might change over time.[29] Indeed, the first line shows that natives with primary education that belong to an experience/time cell with a large proportion of immigrants are less likely to work in blue-collar occupations, which are almost systematically the worst paid occupations.[30] Instead, the correlation is reversed for the proportion of natives with primary education who work as technicians. For individuals with secondary education, the correlation also goes from negative to positive as we move away from blue-collar occupations, and

[29]The probability to be in a white collar occupation for a university graduate was much higher in 1962 than in 1999 for example.

[30]The two only exceptions are the technicians in agriculture, which happen to be paid less than blue-collars in certain industries, and blue-collars in "oil, electricity, and energy", which are better paid than technicians in certain industries.

Table 11: The impact of the proportion of immigrants within an education/experience/year cell on the occupational distribution of natives within the cell

	Blue Collar Occupations	Technicians	White Collar Occupations
		Primary Education	
Immigrant Share	-9.34***	.745***	0.189
	(0.228)	(0.219)	(0.172)
		Vocational Education	
Immigrant Share	-6.54***	3.67**	2.87**
	(2.1)	(1.64)	(1.28)
		High-School	
Immigrant Share	-1.45	-1.25	2.69**
	(1.18)	(0.743)	(1.02)
		University Graduates	
Immigrant Share	-0.236	-4.66***	4.89***
	(0.332)	(0.656)	(0.809)

Notes: This table regresses the proportion of natives in specific occupations within an education/experience/year cell against the proportion of immigrants in the cell. Each regression includes cohort fixed effects using the definition of cohorts in Table 5. Each regression is based on 40 observations.*, ** and *** denotes significant at respectively 10%, 5% and 1% level. Sources: Census of Population 1968-1999, FQP 1970, 1977 and LFS 1982, 1990, and 1999.

the same pattern is observed for individuals with college education when going from technical occupations to the better-paid white-collar occupations.[31]

Regional Level The most obvious source of concern with the previous results is that the lagged immigrant share may not be a valid instrument. In the presence of persistence cohort effects, the error term might be correlated at the cohort level, in which case the lagged immigrant share would not be a valid instrument because it would also be related with unobserved persistent over time cohort effects. As a robustness check, we turn to the area approach and exploit the geographic variation in the occupational premium by adding a regional dimension to our education/experience cells. Importantly, the use of up to 25% census extracts guarantees that sampling errors are relatively small even for cells within regions with few immigrants, and thus reduces the extent of potential attenuation biases provoked by sampling error. Table 12 reports the determinants of the occupational premium of natives across education/experience/region cells, while Table 13 presents analogous regressions for the relative occupational premium of natives (Panel A) and the occupational premium of immigrants (Panel B). Different sets of

[31] Wages in every white-collar occupation are systematically higher than wages in any technical occupation.

Table 12: Regional Regressions: Occupational Premium of Natives

	Dependent variable: *Occupational premium of natives*	
Log Natives	-0.060***	-0.026***
	(0.006)	(0.005)
Log Immigrants	-0.003	0.000
	(0.003)	(0.003)
Overid. (pvalue)		0.85 (0.35)
FE included	(region x education x experience),(region x t), (education x t), (experience x t), (region x education)	
Log Natives	-0.071***	-0.020***
	(0.007)	(0.010)
Log Immigrants	-0.006*	-0.018**
	(0.003)	(0.008)
Overid. (pvalue)		0.005 (0.81)
FE included	previous and (education x experience x t)	
N	2445	1756
Estimation Method	WLS	2SLS

Notes: This table reports regression results of models relating the native occupational premia across education/experience/region cells with the log of natives and the log of immigrants. Region, education, year and experience fixed effects are included in all regressions. Regions are defined using French administrative regions (*régions*). Occupational premia are calculated using the interaction between 3 professional status and 100 industries. Estimations in column 2 use as excluded instruments the counterfactual log of immigrants using predicted settlement patterns of immigrants calculated using either the previous census or 1968 as a reference year in equation (10). WLS regressions are weighted using the number of immigrants per cell. Robust heteroscedastic standard errors reported in parenthesis are adjusted for clustering within education/experience/regions cells. *, ** and *** denotes significant at respectively 10%, 5% and 1% level.

Table 13: Regional Regressions: Relative Occupational Premium and Occupational Premium of Immigrants

Dependent variable:		
A. Relative occupational premium		
Log Natives	-0.049***	-0.033
	(0.007)	(0.032)
Log Immigrants	0.019***	0.051***
	(0.004)	(0.011)
Overid (p-value)		2.96 (0.08)
FE included	(region x t), (education x t),(experience x t), (region x education), (region x education x experience)	
Log Natives	-0.069***	-0.086
	(0.011)	(0.064)
Log Immigrants	0.008	0.002
	(0.005)	(0.034)
Overid (p-value)		2.61 (0.10)
FE included	previous and (education x experience x t)	
B. Occupational premium of immigrants		
Log Natives	-0.010	0.009
	(0.008)	(0.033)
Log Immigrants	-0.023***	-0.051***
	(0.003)	(0.011)
Overid (p-value)		1.71 (0.19)
FE included	(region x t), (education x t),(experience x t), (region x education), (region x education x experience)	
Log Natives	-0.001	0.071
	(0.012)	(0.069)
Log Immigrants	-0.014***	-0.021
	(0.005)	(0.034)
Overid (p-value)		2.01 (0.15)
FE included	previous and (education x experience x t)	
Estimation Method	WLS	2SLS
N	2445	1756

Notes: See Table 12.

controls are included in each specification using several possible two ways and three ways interactions between year, region, education, and experience. Column 2 in each table report 2SLS estimates in which the log of immigrants is instrumented using two counterfactual shift variables based on different settlement patterns across cities described in section 2. In all these regressions, the instruments for immigrant shocks prove to be strong with a Cragg-Donald F statistic (not reported) systematically larger than 100, compared to the critical value from Stock and Yogo (2005) of about 20. In most specifications, the instruments also pass conventional exogeneity tests except the in specification including interactions between education, experience and year which use the log of natives as a dependant variable.

In the model of the upper panel of Table 12, results indicate that the occupational premium of natives is negatively related with the number of natives in the cell, just as in national regressions.[32] However, in contrast with national regressions, the log of immigrants is generally non-significantly correlated with the occupational premium of natives, and in the few cases in which a significant correlation is found, this correlation turns out to be actually negative.

As for the determinants of the occupational premium of immigrants and the relative occupational premium, regional level results are very similar to the national estimates. In particular, Table 13 shows that the immigrant occupational premium is still negatively and significantly correlated with the log of immigrants,[33] and that the relative occupational premium is positively correlated to the log of immigrants. Moreover, in regressions in which the log of immigrants is instrumented, point estimates of the impact of the log of natives are much lower and measured much less precisely while the estimated impact of the log of immigrants is higher than in OLS estimates in some specifications. The results nonetheless strongly confirm there are different specialization patterns across occupations between immigrants and natives across cells within regions and that immigrants tend to compete with immigrants rather than with natives.

Overall, from these results, we find that the different specialization patterns across occupations observed at the national level also hold at the regional level with a different IV strategy

[32]Interestingly, in contrast with the national level results reported in Table 10, point estimates are now lower in those specifications where the immigrant share is instrumented (columns 2 and 3). This result might come from a downward bias of area approach estimates due to natives' outmigration from the regions where immigrants settle in.

[33]Interestingly, point estimates are now larger than similar estimates at the national level which may suggest that internal mobility of immigrants is less of a problem in regional models compared with natives.

to deal with the potential endogeneity of the immigrant share. Immigrants belonging to education experience regions cells with more immigrants tend to work on average in occupations characterized by lower wage premia. In addition, the difference between the premia of natives and immigrants is still positively correlated with the number of immigrants. Therefore, we believe it is unlikely that aggregate regressions at the national level are significantly biased by a positive selection of immigrants within cells.

4 Conclusion

Within the Borjas specification, immigration is shown to have a strong positive effect on the wages and employment of French natives. This result is shown to be robust to controls for the potential endogeneity of the immigrant share or to the introduction of a geographical dimension to education/experience cells. However, the strong positive correlation between the number of natives and the number of immigrants suggests that the immigrant share is not perhaps the best measure of the immigration shock in the case of France. When the log of immigrants is instead used as a measure of that shock, the effect of immigration on wages remains positive, but becomes much smaller. Finally, we provide evidence that the positive effect of immigration on natives' wages and the differential impact of the number of immigrants and the number of natives on natives' wages is at least partly due to the fact that immigration helps natives climb the occupational ladder.

4.1 Appendix 1: Definition of the variables

The number of natives and immigrants per education/experience cell are computed using 25% extracts of the French census in 1968, 1982, 1990, and 1999, a 5% extract in 1962 and a 20% extract in 1974. Sampling weights are used in all the calculations. The analysis is restricted to men aged 18-64. A person is defined as an immigrant if he is a noncitizen or a naturalized French citizen born abroad.

Education

The education variable reported in the Census indicates the diploma received by the individual. We use the variable *fr62a-educ* and *fr62a-diploma* in the 1962 Census, *DIP* in the 1968, 1975 and 1982 censuses, *DIPL1* in the 1990 Census and *DIPL* in the 1999 Census. We classify individuals in four educational groups depending on their diploma: Primary education, Secondary education, High School and College. Primary education level includes individuals which declare to have no diploma and people having the primary school certificates (DFEO and CEP). Secondary education level includes individuals which report to have a diploma of a level equivalent to the *Diplôme National du Brevet* (BEPC) and includes individuals holding a CAP, a diploma of CAP level, a BEP, a BEPC, or a BEPS. High school education includes individuals who have a diploma equivalent to the Baccalaureate. This group also includes general, professional or technical Baccalaureate graduates, *Brevet Professionnel* graduates, *Brevets de Technicien* graduates, *Brevets d'Enseignement Commercial*, *Industriel*, *Social*, *Hotelier*, *Agricole* graduates, *Brevet d'Agent Technique*, BT and BA graduates. College level includes all individuals with a diploma of a level superior to the Baccalaureate which includes *diplômes paramédicaux et sociaux*, BTS, DUT, DEST, *Diplômes d'université de Premier*, *Second et Troisième Cycle*, *Grandes Écoles*, *Écoles d'Ingénieurs*, etc.

Monthly Wages

The data used to compute the average wage by experience level and educational level come from the 1964, 1970 et 1977 survey FQP (*Formation et Qualification Professionnelle*) and from the French labor force survey (LFS) of 1982, 1990 et 1999. The 1964 FQP survey took place between November 1963 and February 1964 and provides information on net annual income from work in 1962 (Degenne et al., 1998). The 1970 and 1977 FQP surveys provide information on the net annual income from work in 1969 and 1976. The LFS provides the net monthly income of the main reference profession of an individual at the time of the survey (April in 1982, January and February in 1990, and March in 1999).

To compute the average wage per cell of experience and education, we include native individuals which report to be employed during the survey, which are wage earners and are employed by the private sector. Because there is no information on the country of birth in the 1964 and 1977 FQPs, natives are defined as individuals who are natural born citizen. We exclude independent workers and civil servants. In the 1982 LFS, there is no variable which distinguishes naturalized citizens from natural born citizens, therefore naturalized citizen born abroad which must be counted as immigrants are included in the sample (according to the 1982 Census, the number of naturalized citizen born abroad is equivalent to 2% of the total number of male workers).

In the 1964 FQP and the 1982 LFS, wages are coded as a qualitative variable. In the 1964 FQP, we impute the annual income in the following way: 3000 for less than 4000 *Nouveaux Francs* (NF), 4500 for 4000-4999, 5500 for 5000-5999, 7000 for 6000-7999, 9000 for 8000-9999, 12500 for 10000-14999, 17500 for 15000-19999, 27500 for 20000-34999, 52500 for 35000-49999, 75000 for 50000 NF and more. In the 1982 LFS, *for the average monthly wages,* we impute 1000 for less than 1000 Francs (F), 1250 for 1000-1499, 1750 for 1500-1999, 2250 for 2000-2499, 2750 for 2500-2999, 3250 for 3000-3499, 3750 for 3500-3999, 4250 for 4000-4499, 4750 for 4500-4999, 5500 for 5000-5999, 6500 for 6000-6999, *7500* for 7000-7999, 8500 for 8000-8999, 9500 for for 9000-9999, 12500 for 10000-14999, 17500 for 15000-19999, 22500 for 20000-24999, 27500 for 25000-29999, 45000 for 30000 F and more.

There is no information on the precise number of hours worked in the FQP surveys. Therefore, we only retain individuals which declare to have been full time employed during the last twelve months in the year preceding the survey. In the LFS, we eliminate individuals which declare not to work full time during the survey week. Average monthly income is obtained from the FQP survey by dividing by 12 the net annual wage income from work. Monthly wages are converted in 2007 euros using the CPI deflator computed by the INSEE. The *average log wage* is obtained by computing the average of the log of the monthly wage over the relevant population. The final sample size used to compute these averages is 5507 for 1964 FQP, 10993 for 1970 FQP, 10906 for 1977 FQP, 21738 for 1982 LFS, 17512 for 1990 LFS and 19556 for 1999 LFS.

Crosswalk tables for industry classifications

We use the industry classification which remained unchanged for the longest period of time in the data. The NAP (*Nomenclatures d'Activités et de Produits 1973*) is used in the 1975,1982 and 1990 censuses and in contemporary surveys (LFS and FQP) from 1974 to 1994. We have created crosswalk tables with other industry classifications to match them with the NAP at the four digit level. The 1959 SIC (*Nomenclature des Activités Économiques - édition 1959*) is used in the 1968 Census and in the 1970 FQP. The NAF (*Nomenclature d'Activité Française*) is used in the 1999 Census and in labor force surveys from 1994 to 2002. For the correspondence between the 1959 SIC and the NAP, we have used the correspondence tables created by the INSEE (INSEE, 1976) in the 1970s. To deal with cases of multiple correspondence, we have used the 1975 Labor Force Survey in which both codes are available to determined the frequency of each correspondence. We then kept the correspondence with the most observations when available. For the match between NAP and NAF, we have used the 1994 LFS in which both codes are also given to establish a match at the four digit levels. Similarly, when several possibilities existed, we have kept the most frequent correspondence. In both cases, the match has been completed manually to include exhaustively all codes in the correspondence table at the four digit level.

Geographical Instrument Based on Settlement Patterns of Immigrants

We distinguish groups of immigrants by using 54 different countries of birth available across censuses. We assign other individuals (less than 5% of immigrants on average) into four regions of birth groups (Europe, Asia, Africa and Other). Because immigrants from some nationalities were very rare during the 1960s in France, particularly immigrants from Asia or subs-Saharan Africa, we compute two different instruments by using either 1968 or the year of the previous census as a reference year. The first instrument captures immigrants flow related to traditional ports of entry of immigrants in France while the second instrument predicts immigration using more recent settlement patterns and takes into account the location choice of nationalities not in France during the 1960s.

4.2 Appendix 2: Education/experience analysis at the regional or county level

We extend the analysis in section 3.1 to define education/experience cells at the level of the 22 regions or 95 *départements* (counties) constituting metropolitan France. Table 14 reports the results of the regressions for the employment-population ratio and the employment-labor force

Table 14: Impact of Immigrant Share on Natives using Geographic Unit x Education x Experience groups

dependent Variable: Employment-Population Ratio	(1)	(2)	(3)
1) Regional Level	0.089**	0.156***	0.017
	(0.045)	(0.030)	(0.022)
2) County Level	0.080***	0.148***	0.011
	(0.029)	(0.015)	(0.013)
dependent Variable: Employment-Labor Force Ratio			
1) Regional Level	0.143***	0.133***	0.010
	(0.023)	(0.020)	(0.013)
2) County Level	0.139***	0.114***	-0.005
	(0.016)	(0.012)	(0.009)
Controls for:			
(region x period), (education x period),	Yes	Yes	Yes
(experience x period), (region x education) fixed effects			
(region x education x experience) fixed effects	No	Yes	Yes
(education x experience x period) fixed effects	No	No	Yes

Notes: The table reports the coefficient of the immigrant share. The dependent variable is the average labor market outcome of a group of workers with similar experience, education and living in the same region or county in a given year. Number of observations 3520 for regions and 12192 for counties. Each observation is weighted by the number of natives per cell divided by the total number of natives of the year. Robust heteroscedastic standard errors clustered by education/experience/geographic unit are reported in parenthesis. Regressions using counties include observations from 1968 to 1990. Regressions using regions include observations from 1962 to 1990. *, ** and *** denotes significant at respectively 10%, 5% and 1% level. *Sources:* Census of Population 1962-1990, FQP 1964, 1970, 1977 and LFS 1982, 1990.

ratio only, given that the small sample size of the FQP and LFS does not allow for the same exercise to be conducted for wages at the regional level and the more disaggregated county level. Column 1 reports the baseline specification. The coefficient for the employment rates are all positive and significant, but smaller than at the national level, as in Borjas (2003). We here also find that the estimates at the more detailed county level are smaller than at the regional level, which seems to confirm that the choice of a smaller geographical location attenuates the effects of immigration. Moreover, given we use 25% extracts of the censuses, we can rule out that this attenuation bias comes from higher sampling errors when estimating the immigrant share across regions. Column 2 adds interactions between regions, education and experience fixed effects, which makes the point estimate bigger and reduces standard errors. Finally, when education/experience/period fixed effects, the point estimates become smaller and statistically insignificant.

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