The Impact of Immigration on the Local Labor Market Outcomes of Blue Collar Workers: Panel Data Evidence[*]

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Abstract

Using a large administrative French panel data set for 1976-2007, we examine how low-educated immigration affects the wages, occupations and locations of natives' workers. Unlike previous work, we focus on very homogeneous groups of blue collar natives working initially in immigrant-intensive industries and who are thus more likely to compete with immigrants. We first show that immigration into locations alters the local composition of the native labor force, as larger immigration inflows into locations are accompanied by larger inflows and outflows of natives to/from these locations. Natives changing location following immigration are negatively selected, while natives changing occupation are positively selected and move to occupations with less routine jobs. Using a balanced sample to control for these composition effects, we find that immigration has no negative impact on employment. However, immigration lowers the median annual wages of natives, particularly in non-tradable sectors such as the construction sector. Moving across locations does not mitigate the negative impact of immigration on wages, while moving across occupations does mitigate it.

[*] We thank the INSEE for having made the data available. The Census data used in this paper are available upon request for researchers from the CMH. The authors accessed the DADS data via the *Centre d'Accès Sécurisé Distant* (CASD), dedicated to the use of authorized researchers, following the approval of the *Comité français du secret statistique*. The views expressed here do not necessarily reflect those of any of the organizations with which the authors are affiliated. We thank Kyle Mangum, Manon Dos Santos and Muriel Roger and seminar participants at Norface, SOLE, IZA-SOLE and CEP (LSE) for very useful suggestions.

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Introduction

A large part of the public concern about immigration in developed countries is a concern about the impact that immigrants might have on the labor market outcomes of natives. However, credibly identifying the impact of immigration poses a significant empirical challenge. While much work has been done, the recent literature has not yet reached a consensus on the appropriate methods which should be used. Importantly, results using alternative identification strategies tend to differ widely while replication exercises across countries often provide conflicting results.

Many previous papers have used fixed and observable individual characteristics such as education and experience to delineate the groups of natives and immigrants in competition (see e.g. Borjas (2003)), or Aydemir and Borjas (2007)). However, recent research has criticized the hypothesis of perfect substitution within education/experience groups. Indeed, if immigrants and natives with similar education and experience levels are not directly in competition, changes in immigrant supply may have little impact on native wages.[4] As a result, most of the negative impact of immigration could be concentrated on narrow groups of natives who compete for jobs similar to the one that immigrants tend to occupy.

A second issue is that most previous studies had to rely on cross-sectional changes at the local level to investigate how immigrant inflows affect native outcomes. If a substantial share of native workers move out of a location in response to immigrant inflows while other workers move in, the interpretation of results from studies using changes in wages within locations will be affected by the selective change in the characteristics of native workers

[4] See

Ottaviano and Peri (2012 and Manacorda et al. (2012) for evidence that immigrants and natives might be imperfect substitutes within education/experience cells in respectively the US and the UK. Peri and Sparber (2009) show that low-skill natives in local labor markets receiving more immigrant inflows tend to specialize in occupations requiring more abstract tasks in response to immigration. Dustmann et al. (2013) show that recent immigrants start working in occupations offering a much lower wage than natives with similar observable characteristics.

across locations.[5] Because native migrants might not be selected randomly from the sending population, it is challenging to separately identify the impact of immigrant inflows on native outcomes if the composition of natives changes significantly when the share of migrants in the population increases.

In this paper we revisit the effect of low-educated immigration on the local labor market opportunities of natives by exploiting detailed information on individual labor market trajectories from a very large administrative panel data of the French labor force over a period of 30 years. This large panel data provides for about 4% of French private sector employees exhaustive information on the wages, occupations, the number of days of work, and the geographical location at the municipality level of each job held during the period 1976- 2007. In contrast to previous work, we also use very large (25%) sample extracts from the Census to estimate changes in low-educated immigrant inflows across locations and to construct our instruments. Using these data, we use the variation in immigrant inflows across different employment zones to investigate how the location and employment outcomes of blue collar native workers have responded to low-educated immigrant inflows.

Using panel data to examine the impact of immigration on the labor market outcomes of natives is attractive for several reasons. A first key advantage is that detailed information on individual labor market trajectories is available. This implies we can identify and focus on the groups of natives which are most likely to be affected by immigrant inflows, namely those who *initially* have a job that low-educated immigrants also tend to occupy. Recognizing that immigrant inflows may affect wages more or less for workers offering different skills in the labor market, the econometric model is estimated separately for natives initially defined as

[5] Using US decennial data, Card (2001) and Cortes (2008) have found no evidence of native outflows in response to immigrant inflows while Borjas (2006), on the other hand, reports strong displacement effect. More recently, using US annual aggregate data, Wozniak and Murray (2012) find that immigrant' inflows are correlated with *declines* in outflows of low skill natives in the shorter run of one year. Recent European studies found stronger evidence of displacement: using Italian data, Mocetti and Porello (2010) find evidence of displacement of low skilled natives following immigrant inflows. For the UK, Hatton and Tani (2005) find consistently negative displacement effects.

blue collar workers across different industries which vary with respect to their share of immigrants.

A second advantage of using panel data is that we are able to control for unobserved heterogeneity of workers by estimating models using a balanced sample. With longitudinal data, we are able to isolate the causal effect of immigration on wages from any compositional change introduced by a correlation between immigrant inflows and changes in the permanent component of unobserved wage heterogeneity in the location.

We investigate the impact of immigrant inflows at the level of 297 consistently defined, fully inclusive Commuting Zones (approximating local labor markets). To assess the importance of composition effects, we first present some new facts on two sources of endogenous selection in response to immigration inflows, namely changes in location and changes in occupation.

First, we find compelling evidence in alternative datasets of a moderate positive correlation between low-educated immigrant inflows on the one hand and both inflows and outflows of blue collar natives in the location on the other. Quantitatively, baseline OLS estimates suggest that a 10 p.p. increase in the immigration rate (defined as the ratio between the number of low-educated immigrants and blue collar natives in the commuting zone) increases the outflow rate of blue collar natives by 1.6 p.p. Interestingly, IV estimates indicate a much larger displacement effect for workers in the most immigrant-intensive industries such as construction.

Second, consistent with evidence from Peri and Sparber (2009) for the US or Ortega and Verdugo (2014) for France, we also find that natives are more likely to move to occupations requiring less routine tasks following an immigrant inflow. However, workers react quite differently across groups, and we do not find any effect on workers initially in the construction sector. The fact that the probability to change occupation following an immigration inflow varies importantly across occupation groups suggests that a substantial share of workers are not able to protect themselves from competition with immigrants by moving to another occupation.

We also find that the selection patterns of the individuals changing location and the individuals changing occupation differ in an important way. Specifically, individuals changing location are negatively selected –i.e. they have lower average wage than the stayers, while those who move to better occupations with less routine tasks are instead positively selected. As a result, selection across locations and occupations affects the composition of occupation groups in an opposite way.

In the second part of the paper, we turn to the impact of immigration on the wages and employment of natives. To isolate the impact of changes in composition from the impact of immigration on wages, we provide estimates using a balanced panel in which the composition of workers is maintained constant across periods and use the initial location and occupation to define several alternative 'treated' groups of natives. We find no evidence of a negative impact of immigration on the average number of days worked or the employment rate. In contrast, we find immigration to be negatively correlated with median annual wages, the effect being the largest for workers in the non-tradable sector, particularly those in the construction sector. For this group, our estimates suggest that an increase in 10 p.p. in the immigration ratio at the local level generates a decrease of 3.6 log points in the median annual wage.

To investigate the consequences of selective out- and in-migration of natives, we compare estimates of alternative models in which location-movers and occupation-movers have been excluded. Such straightforward comparisons indicate how much self-selection across locations and occupations affects the previous estimates. Overall, we find that estimates excluding location-movers are not significantly different to the ones in which they are included. On the other hand, we obtain a much larger negative impact of immigration when the sample only includes the selected group of workers not changing occupation. Overall, these results suggest that immigration decreases the price of particular skills in the labor market but that the reallocation of a share of natives to different occupation attenuates the final effects on native wages, as argued by Peri and Sparber (2009).

As far as we know, papers using individual panel data to estimate the impact of immigration are still relatively rare. The spirit of our analysis is similar to Bratsberg and Raaum (2012) who use Norwegian panel data to estimate the impact of immigration on workers in the construction sector. As in this paper, they find evidence that immigration lowered the wages of competing workers in the construction sector. Importantly, they also find selective attrition of workers across occupations within the construction sector to be important, such that it may mask the causal wage impact of immigration on wages. Distinct from their work, we focus on local labor markets, which have been used in much of the previous work, and include in the analysis a much larger group of workers in order to investigate potentially important heterogeneities in the impact of immigration. We also extend the literature by examining into detail the potential confounding role of natives' mobility across both locations and occupations. Importantly, we also investigate the selection patterns of stayers and movers along location and occupation. While the literature on the local labor markets impact of immigration is large, to the best of our knowledge, no other study has combined the advantages of a large administrative panel data, and the simultaneous focus on outcomes such as locations or occupations found in the present paper.

The remainder of the paper is organized as follows. The first section presents the data and provides some descriptive evidence on immigration into France. The second section discusses the empirical framework. The third section investigates the relationship between native locations and occupations and immigrant inflows. The fourth section examines the impact of immigration on employment and wages. The last section concludes.

I) Data and descriptive evidence

Data Sources

Our primary source of data for the analysis comes from the matched employer-employee panel DADS (in French *Déclaration Annuelle de Données Sociales*) collected by the French National Institute for Statistics (INSEE).[6] The sample contains earning histories for all individuals born in even-numbered years in October. Annual DADS data are available from 1976 to 2007 except for 1981, 1983 and 1990 were the data were not collected.

Three features of this dataset make it well-suited for studying the impact of immigration: first, DADS data are collected from compulsory fiscal declarations made annually by all employers for each worker and are thus considered very reliable.[7] The annual wage data is considered of very good quality: the reporting, made by the employer, is used to compute the income tax of the worker. Employers have no incentives to misreport wages as this is severely punished with fines. Second, DADS data being an administrative panel data collected for fiscal purposes, involuntary attrition has been evaluated to be modest.[8] Most of the attrition comes either from an exit from a sector covered by the DADS or a supply of zero days of work in a given year. Third, the sampling size is very large: we have information on wages for 350,000 individuals per year over the period, representing about 4% of the population working in the private sector.[9]

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[6] See e.g. Abowd et al. (1999) or Combes et al. (2008) for recent examples of papers using this dataset.

[7] Not all the sectors of the economy are covered each year and the degree of coverage increases over time. In particular, civil servants and most large public sector firms are excluded until the 1990s. Using LFS data, we estimate that they represented approximately 8% of the labor force during the 1980s.

[8] Koubi and Roux (2004) document that most of the temporary attrition from the DADS panel corresponds in practice to inactivity or a work outside of the DADS covered sector (such as self-employment, or work in the public sector until the 1990s). Attrition in the DADS panel has also been shown to be much lower than in typical survey-based panels such as the European Community Household Panel (ECHP)(Royer (2007)).

[9] The sampling size doubles in 2002 when individuals born in odd-numbered years in October are added to the sample.

The data contains a unique record for each employee-establishment-year combination. For each individual job spell of any length in a given firm, the DADS collects information on earnings, whether the job was part or full-time, the number of days of work and the location at the municipality level. One drawback is that information on the number of days of work and the precise number of hours worked appears to be rather noisy.[10] A relatively large share of workers is reported to have worked full-time full year but have wages well below the minimum wage. This creates a limitation to evaluate daily wages or changes in number of days worked.

We aggregate each job spell to obtain the total annual income and number of days of work within a year. We retain information on occupation and industry of the job held during the largest number of days. Note that education is missing from the data. Another important point is that there is no information on nationality in the DADS but the data indicate whether an individual is born abroad. We define as natives, in this dataset only, individuals who are born in France and exclude individuals who are born abroad from the native sample.[11]

Because of this last limitation, we do not rely on DADS data to estimate changes in the number of immigrants across local labor markets over time. The lack of information on the country of origin makes it impossible to construct an instrumental variable for changes in the immigration ratio using differences in settlement patterns across immigrant groups. Instead, we rely on Census data to estimate the changes in the number of low-educated immigrants across commuting zones. Censuses of the population took place in 1975, 1982, 1990, 1999 and 2007. An important advantage of this dataset is that we use 25% extracts (20% in 1975)

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[10] Information on whether an employment spell was full or part time is available over the entire period but the number of hours worked is only available after 1993 (see Aeberhardt et al. (2011) for a discussion). Following the current practice, we have chosen not to use it.

[11] Many French-born citizens who should not be counted as immigrants were born in Algeria before independence in 1962: using the census, their share among 18-65 years old natives is 2.2% in 1982 and 1% of in 2007. More generally, the share among natives of French-born citizen who are born abroad is rather small and declining over time: 4.4% and 3.2% in respectively 1982 and 2007. Since we are not able to distinguish them from immigrants, they are excluded from the DADS sample of natives.

of the Census population to compute changes in the immigrant ratio across locations over time. Such large sample size are essential for an analysis of the impact of immigration since it renders the results immune from attenuation biases as identified in Aydemir and Borjas (2011). As is conventional, an immigrant is defined as a foreign-born individual who is a non-citizen or naturalized French citizen.

Local labor markets are defined using the 2010 definition of commuting zones (*zones d'emploi*). Commuting zones are designed by the INSEE to approximate local labor markets using information on daily commuting patterns. They aggregate the 36 699 existing French municipalities into 297 labor market regions.[12]

Our empirical implementation uses variations in low-educated immigrant inflows across commuting zones in France from 1975 to 2007. We estimate first-differenced models in which we relate changes in native labor market outcomes obtained from the DADS data with changes in the share of low-educated migrants obtained from the Census data using years in which both census and DADS data are available.[13] Low-educated immigrants are defined as immigrants with a level of education below high-school graduation. Since DADS data does not contain information on individuals out of the labor force, we focus on prime-aged male workers aged more than 25 and less than 54 who have relatively strong labor market attachment and for whom non participation during a full year is less likely to be a major issue.[14] This implies we concentrate on individuals aged 25 to 45 in census year *t* and 32 to 52 or 34 to 54 in census year *t+1*, where t is a census year and *t+1* the year of the next census,

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[12] Commuting zones are also used with the DADS data by Combes et al. (2008) and Combes et al. (2012). They are defined in a consistent way over time. We drop commuting zones from Corsica (less than 0.3% of the population), as a change in the département code in 1976 complicates their matching across datasets over time.

[13] Given DADS data were not collected in 1975 and 1990, we match census data from the 1975 and 1990 census with respectively the DADS data from 1976 and 1991.

[14] We also apply these restrictions to avoid issues with changes in retirement age over time. Young workers are also eliminated to avoid problems with potentially endogenous labor market participation in case immigration influences education decisions (see Hunt (2012) or their employment probability (see Smith (2012).

and that we consider changes in the number of immigrants within commuting zones over periods of 7 to 9 years.

Immigration in France: Descriptive Evidence

According to the last census, in 2007, 5.2 million immigrants lived in France, which amounts to 8.3% of the population. The share of immigrants in the population is thus lower than in the U.S. and the U.K. (respectively 11.5% and 11.9%, see Dustmann et al., 2013, p. 11). However, from 1975 to 2007, France experienced an increase of 5 p.p. from 13% in 1975 to 18% in 2007 in the share of immigrants among the group of male workers[15] with a level of education below high-school. The geographical origin of immigrants also changed during the period: the share of European immigrants decreased from about 60% in 1975 to only 32% in 2007.

Table 1 reports the share of foreign born workers among blue collar workers in 1999 in the tradable and non-tradable sectors for the country as a whole and for some large cities (see Appendix for details on industries and occupation classifications used in the paper).[16] As shown in the table, low-educated immigrants tend to be overrepresented in some sectors and regions, particularly in the non-tradable sector. The share of foreign born workers is 4 p.p. and 10 p.p. higher in respectively the non-tradable sector and the Construction sector relative to the tradable sector. These figures suggest that competition for jobs with low-educated immigrants may be strongest in the non-tradable and construction sector.

Immigrants are also unevenly distributed across regions: while only 3% of blue collar workers are foreign born in Brittany in the non-tradable sector, the share of foreign born is 33%

[15] Unless otherwise indicated, figures in this section male workers aged 18-64 which are not students or in the military.

[16] We rely on standard classification systems of industries. See appendix for details. Following Hanson and Slaughter (2002) and Dustmann and Glitz (2012), the group of tradable industries includes manufacturing, agriculture, mining, finance and real estate.

in Paris. Similarly, the share of foreign born blue collar construction workers is 45% in Paris compared to 5% in Brittany. However, Table 2 indicates that in both regions, the share of foreign born workers expanded in the Construction sector in the last 30 years.

II) Theoretical Framework

Immigration may impact the labor market outcomes of natives through several channels which are interrelated, including wages, location or occupations. Here we discuss these channels. Assuming a CES production function with different occupation groups each of them aggregating individuals heterogeneous in their labor productivity, the period *t* log wage for individual i in local labor market l and in occupation group k can be written as (see Appendix):

$$\log w_{it}(k,l) = \log B_{klt} - \frac{\gamma_k}{\sigma}\frac{I_{lt}}{N_{klt}} + X_{it}\phi + \alpha_i\,, \qquad (1)$$

where σ is the elasticity of substitution across occupation groups, α_i is individual *i*'s unobserved (and constant) productivity, X_{it} is a set of individual observable characteristics, N_{lt} is the number of natives in occupation group *k* and I_{lt} the number of low-educated immigrants in location l. We discuss below how we empirically define these occupation groups. A key point is that, as in Smith (2012) or Dustmann et al. (2013), we do not pre-allocate low-educated immigrants to a particular group but estimate the response of various native groups to a change in the share of low-educated migrants in the location. To introduce heterogeneity in the impact of immigration across groups in the simplest way, we follow Dustmann et al. (2013) and assume that a share γ_k of low-educated immigrants have a skill level corresponding to the occupation group k, and that they are perfect substitutes within occupation groups.

Workers might endogenously adjust to immigration by changing location as argued by Borjas et al. (1997) or occupation as argued by Peri and Sparber (2009) and Amuedo-Dorantes and de la Rica (2011). If immigration changes the relative price of skills in the labor market, some workers might move to another location or to another occupation in response to immigrant inflows. To illustrate in a simple way how endogenous self-selection may confound the impact of immigration in cross-section regression in this framework, assume workers differ in their ability to move across locations as in Moretti (2011) or Beaudry et al. (2010) or in their ability to move across occupations. As a result, individuals changing location or occupation are not a random sample of the initial population of workers. Assume next that native outflows are such that the efficiency units of labor supplied by natives change by $\Delta N_{klt} = -\epsilon_k \gamma_k \Delta I_{lt}$ when the share of immigrant increases by ΔI_{lt} in the location.[17] The parameter ϵ_k is the share of native net outflows in group k with respect to a change in immigrant labor supply. When $\epsilon_k = 1$, there is perfect displacement, while when $\epsilon_k = 0$ there is no response. This implies that changes in the average log wage $\Delta\overline{\log w_{klt}}$ of natives in occupation group k, location l and period t can be expressed as:

$$\Delta\overline{\log w_{klt}} = \Delta \log B_{klt} + \beta_k \Delta p_{lt} + \Delta X_{klt}\phi + \left(\alpha_{klt+1} - \alpha_{klt}\right) \qquad (2)$$

where $\alpha_{klt} = \frac{1}{N_{klt}} \sum_{i \in k,l} \alpha_i$ is the average productivity of workers and $X_{klt} = \frac{1}{N_{klt}} \sum_{i \in k,l} X_{it}$ is the average individual observable characteristic. The term Δp_{lt} captures the change in the share of low-educated migrants in the location while the term $\left(\alpha_{klt+1} - \alpha_{klt}\right)$ captures changes in the unobserved productivity of workers in occupation group k. There is positive selection correlated with immigrant inflows if $cov\left(\alpha_{klt+1} - \alpha_{klt}, \Delta p_{it}\right) > 0$ and negative selection otherwise.

[17] The previous equation is obviously a reduced form. Modeling the sorting of workers across locations is beyond the scope of this paper.

In this simple framework, the parameter $\beta_k = \frac{\gamma_k}{\sigma}(1-\epsilon_k)$ is a function of the elasticity of wages to the labor supply of immigrants, and of the elasticity of mobility of natives. If mobility costs are sufficiently low for a large number of individuals, that is $\epsilon_k = 1$, native outflows will equalize wages across locations and thus immigration does not have an impact on the *local* wages of natives, but only at the national level, as in Borjas (2006). Instead, if mobility costs are substantial, native internal mobility might not be sufficient to offset the local effect of immigrant inflows on wages. To evaluate the importance of such channels, we test for the impact of immigration on location and occupation and investigate the patterns of selection of location and occupation-movers.

Econometric Model

To take the previous equations to the data, we need to make some additional assumptions. We assume, as common in the literature, that changes in $\log B_{klt}$ over time in a given location and occupation can be decomposed by a full set of fixed effects. Then, equation (A) and (B) lead to simple regression models of the form:

$$\Delta y_{klt} = \beta_k \Delta p_{lt} + \nu_k \Delta Z_{lt} + \phi_k \Delta X_{klt} + \gamma_{kt} + \gamma_{kr} + \epsilon_{klt} \tag{3}$$

where Δy_{klt} is the change in a given outcome between two periods for occupation group k in location l, γ_{kt} are time fixed effects and γ_{kr} are region fixed effects. The vector Z_{lt} contains several location and industry specific factors varying over time. Following the literature,[18] the term Δp_{lt} in the empirical model is defined empirically as the change in the low-educated immigrant ratio with respect to the initial number of blue collar workers in the location: $\Delta p_{lt} = \frac{I_{lt+1} - I_{lt}}{N_{l,t}} e_{I_{lt+1}>I_{lt}}$. The use of a similar numerator across occupation groups facilitates the

[18] See e.g. Card (2001), Card and DiNardo (2000), or Mazzolari and Neumark (2012).

interpretation of the results given the size of groups might vary widely. The term $e_{I_{lt+1}>I_{lt}}$ is an indicator function which is equal to one if the number of low-educated migrants is strictly increasing in the location and is zero otherwise. We condition the immigration rate to be positive to avoid our results to be affected by the rare locations and periods in which the numbers of low-educated migrants decrease in the population.

The model is estimated by pooling multiple decades as stacked first differences. Because the model is estimated in differences, it eliminates time-invariant wage differences across occupation groups and locations that may be correlated with the share of immigrants. The specification also includes changes in average individual-level demographic controls (X_{klt}) and changes in area level controls as well (Z_{klt}). The additional controls included in the regressions are the changes in the share of white collar and blue collar workers, the share of workers in construction, the overall share of workers in manufacturing industries and the average age of workers. The model also includes regional fixed effects. As in Dustmann and Glitz (2012) or Smith (2012), regressions are weighted by the number of observations used to compute the dependent variable: this implies that we weight first-differenced equations by $(1/N_{klt+1}+1/N_{klt})^{-1/2}$ where N_{lkt} is the number of observations used to compute the outcome variable.[19]

Native Groups' Definition

Equation (2) makes clear that, absent a strategy for isolating variations in wages that are independent of changes in the average unobserved α_i in the occupation, changes in wages reflect both the impact of immigration on the supply of labor and on the unobserved average productivity of workers. To get rid of the change in unobserved characteristics of workers, we

[19] This formula comes from straightforward calculations of the variance of a first-difference variable measured with errors under the assumption that the measurement error is proportional to the number of observations and is independent across years.

adopt a simple empirical strategy. The panel aspect of our dataset allows us to define the ‘treated’ occupation group of natives by their *initial* occupation and location.

Using the initial occupation to define occupation groups has several crucial advantages. Natives initially sharing the same occupation are more likely to offer in the labor market a more similar set of skills. Our rich dataset allows us to focus on narrow groups of workers who are more likely to compete with low-educated migrants, namely those in occupations with a larger share of immigrants. If the effect of immigration on wages differs importantly across groups of natives, it might be important to allow for a different effect.

We also control directly for changes in unobserved heterogeneity through the use of a balanced sample in which the composition of natives included in the sample is maintained constant over time. A second interest of our approach is that our strategy controls directly for changes in unobserved heterogeneity through the use of a balanced sample. Estimates of the impact of immigration obtained from a balanced sample are by definition not driven by an endogenous change in the composition of natives in the occupation group.

Occupation groups are defined here by using the interaction between being a blue collar worker and working in a given industry in the initial period. We use four different groups. We define a first group pooling all blue collar workers to estimate the average effect of immigration on these workers. Two other groups are defined by distinguishing between workers in the tradable and non-tradable industries. Finally, we define a fourth group isolating workers from the construction sector from the non-tradable industries group. If the supply effect of immigration differs across groups of natives, we should expect a larger effect on workers initially in non-tradable industries, particularly in the construction sector. On the other hand, if blue collar workers are all perfect substitutes in production, then we expect the impact of immigration to be similar across groups.

Identification

As discussed previously, it is very unlikely that immigrants' geographic settlement decisions are exogenous to local labor market conditions. If immigrants settle disproportionately in areas with better local labor market conditions, then ordinary least squares (OLS) estimates of β_k will be biased. One important concern is the possibility that pre-existing trends are correlated with both changes in the immigrant ratio and changes in the variables of interest. If this is the case, the estimates presented here may simply be a spurious correlation. To deal with this issue, the model includes a control for regional specific trends γ_r for 22 French regions. Due to the inclusion of a vector of regional dummies γ_{kr}, the coefficient of interest β_k is identified by within regional variation. The inclusion of regional dummies means that any confounding factor would have to vary within region over time. Including these fixed effects thus addresses some of the concerns raised by Borjas et al. (1997) when one does not control for the various confounding factors affecting outcomes across locations.

As in Card (2001) and Cortes (2008), our identification strategy uses the initial proportion of co-nationals in the commuting zone as an instrument for future immigrant inflows. Specifically, the predicted number of low-skill immigrants in region r is given for each census year t by

$$\hat{I}_{lt} = \sum_c \left(\frac{I_{cl,t-1}}{I_{c,t-1}} \right) * I_{ct} = \sum_c \lambda_{ct-1} I_{ct}$$

where $\frac{I_{cl,t-1}}{I_{c,t-1}} = \lambda_{cl}$ is the proportion in the previous census date $t-1$ of country c immigrants, including both low and high skill immigrants, living in region l, while I_{ct} is the total number of immigrants from country c in France in year t. Given the large sample size of the census, 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. Following Hunt and Gauthier-Loiselle (2010), we explicitly determine λ_{ct-1} using immigrants from all education and experience levels to have a greater role of geography and ethnic networks. By doing so, our aim is to give less importance to economic factors that might attract workers with low levels of education and experience specifically in a given region. Because the endogenous variable is a percentage, we define our final instrument by using the change in the number of predicted immigrants in the location divided by the initial number of natives, to define our final instrument as: $\frac{\hat{I}_{lt+1} - \hat{I}_{lt}}{L_{lt}} e_{I_{lt+1} > I_{lt}}$

The validity of the instruments used to predict changes in the immigrant ratio over time is examined in Table 3. Observations correspond to changes between census years, i.e., 1975-1981, 1981-1990, 1990-1999, and 1999-2007.

Column (1) reports estimates from a simple bivariate model while column (2) includes a full set a control variables. In both specifications, the coefficient is positive and strongly significant. A comparison between columns (1) and (2) indicates that adding the control variables lowers by a third the estimated parameter but also raises the precision of the estimate. In column (3), we examine results from unweighted estimates: the coefficient declines by a fourth but still remains statistically significant. Overall, the Fisher statistics of the instrument indicate it is reasonably strong across the various specifications. With F-statistics greater than 10 in most specifications, they easily pass the weak instrument test.

III) Immigrant Inflows and Natives' Mobility Patterns

Before investigating the impact of immigration on wages and employment, we first provide evidence on the relationship between immigrant inflows and natives' location and occupations. In contrast with the existing literature, the panel dimension of the data allows us to focus on natives defined by their initial occupation and to investigate selection patterns. In a first and a second subsection, we investigate the correlation between immigrant inflows and changes in locations and occupation of natives. In a third subsection, we look at the selection patterns of movers in an attempt to understand how selective change in location and occupation affects the composition of natives labor force within locations and occupations.

Local labor market mobility

We begin by assessing the relationship between local immigrant inflows and native inflows and outflows. A simple accounting identity relates the net annual change in native total population ΔN_{klt} of occupation group k in location l with the number of individuals who moved into the location (I_{klt}) and the number of individuals who left the location (O_{klt}): $\Delta N_{klt+1} = I_{klt+1} + O_{klt+1}$.[20] Following Card (2001), Card (2009) or Cortes (2008), we estimate separately for each occupation group k the model of Eq. (3) in which the dependent variable is either the inflow rate I^k_{lt+1} / N_{klt} or the outflow rate O^k_{lt+1} / N_{klt}.

Panel 1 in Table 4 shows the results for different groups of industries. Within each panel, the first line provides OLS results while the second line reports 2SLS results. For all groups of workers, with the exception of blue collar workers in the tradable sector, both IV and OLS results indicate there is a positive correlation between immigrant inflows and native outflows in the initial location. OLS results indicate that an increase of 10 p.p. of the immigration rate into the location is associated with an increase in outflow rates of 0.7 to 0.9 p.p. depending on the group. On the other hand, IV estimates are up to four times larger than OLS estimates. Interestingly, the estimated effects are much larger for blue collar workers initially in immigrant intensive sectors such as those in the non-tradable sectors and in the construction sector: we find that an increase of 10 p.p. in the immigration rate raises the share of movers by 1.6 p.p. for blue collar workers and by 3.6 p.p. for workers in the construction sector.

[20] Outflows are computed by using information on the occupation of the individual in the period t+1, and whether this individual has changed location in t, independently of her occupation in period t. Inflows are computed by using the number of individuals in the occupation in period t+1 who worked in a different location in period t independently of their initial occupation.

Turning now to the relationship between variations in the immigrant ratio and native inflows, OLS results indicate for all occupation groups a strong positive correlation. Parameter estimates are remarkably similar across groups of industries. The OLS estimates suggest that an increase in 10 p.p. of the immigration rate is correlated with an increase of 1.7 p.p. in the inflow rate of natives into these occupations. These parameter estimates imply that the arrival of 100 immigrants into the location is correlated with the exit of 16 native blue collar workers and the entry of about 15 native blue collar workers.[21] However, there is no strong evidence for a causal effect on native inflows. While 2SLS estimates are positive and not very different from OLS estimates, they are measured very imprecisely and are not significantly different from zero.

The previous results have several limitations related to the characteristics of the DADS data. The sample only includes individuals with a positive number of hours worked in the private sector in both periods to compute inflows and outflows. Selective attrition to nonparticipation or to a sector not covered by the DADS data could bias our results if immigration is correlated with a large share of native workers dropping out of the labor market or moving to the public sector. To address this concern, we assess the robustness of the previous results by using alternative inflows and outflows rates computed with the French census. An important advantage of the Census data is that it contains the entire population and also includes retrospective information of the location at the municipality level at the time of the previous census. Unlike in the DADS data, information on the initial occupation of native workers is not available in the Census. Instead, we define groups by using information on education and use information on the previous location to define inflows and outflows rates across commuting zones for different education groups. We use four education groups: two

[21] When the model is estimated using blue collar workers, the native outflow rate and the immigrant inflow rate are both divided by the initial number of blue collar workers in the location.

low skilled groups, primary or secondary education, and high-school and university graduates.[22] To be able to make a comparison with the previous estimates, our dependent variable is, as previously, the change in the share of low-educated migrants over the initial number of native blue collar workers.

Consistent with the previous evidence, Census data estimates in panel 2 of Table 4 strongly indicate a positive correlation between both outflows and inflows for low skilled workers. OLS estimates are slightly lower than those obtained with DADS data, indicating an increase in 0.4 p.p and 1.1 p.p. for respectively inflows and outflows for an increase in the immigrant ratio of 10 p.p. As previously, 2SLS estimates are only statistically significant for outflows. The estimated IV coefficients are also much larger than the corresponding OLS estimates, indicating an increase of about 2.4 p.p. and 2.7 p.p. of the share of movers for respectively primary and secondary education workers for an increase of 10 p.p. in immigration rate.

Taking the previous estimates together, three things are clear. First, immigrant inflows appear to be positively correlated with both larger inflows and outflows of native blue collar workers and of low skilled natives across employment areas. The evidence also suggests that only native outflows seem to be causally related to immigrant inflows. Second, the fact that there are two opposite inflows and outflows indicates that immigration is correlated with a change in the composition of native blue collar workers in the location. Our results point to the evidence of a much stronger displacement effect on native workers initially in jobs more likely to be taken by low-educated immigrants. Third, the fact that immigrant and native inflows are also positively correlated indicates that common positive economic shocks might drive both native and immigrant location choice. This correlation between immigrant location

[22] See the Appendix for details on the construction of these education groups.

choice and local economic conditions should bias estimates of the impact of immigration on labor market outcomes of natives.

Occupational Mobility

Next, we examine the impact of immigration on the occupations of natives. Following the literature, we do not examine whether immigration impacts the probability to change occupation but whether natives are more likely to move to better quality occupations in locations with larger immigrant inflows. To capture changes in the skills supplied across occupations over time, we focus on changes in the average routine to abstract intensity of tasks performed in the occupations.[23] The task contents of an occupation provides an approximation of the basic skills required to perform it (Autor et al. (2003),Acemoglu and Autor (2011),Goos and Manning (2007)). To interpret the parameter estimates, our routine to abstract intensity index variable is normalized to have an average of zero and a standard deviation of one across the distribution of occupations. Note that, in the initial period, blue collar workers can be in one of the 6 distinct occupations that we have in our classification.[24] Within the blue collar workers group, the occupation with the lowest routine to abstract skill intensity is "*laborer*" with an index of 0.51 while "*machine operators*" have an index of 1.30. In the final period, there is no restriction and workers initially in the blue collar worker group may be in any kind of occupation.

Table 5 shows the results. Within each panel, the first column provides intent to treat estimates using all workers initially in the occupation group, including those who have moved to another location or occupation. In the second column, those moving from the location have been excluded while the third column also excludes those who are not in the same occupation

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[23] Abstract tasks are "complex problem solving" while routine tasks require repetitive strength and motion and non-complex cognitive skills and thus do not require good language skills. Data on task intensity come from the abstract and routine task intensity indexes calculated by Goos et al. (2010, Table 4 p.49) from the Occupational Information Network (ONET) database that we have matched manually with French occupations classifications. See Appendix for details.

[24] See Appendix for details.

group. Finally, the last column uses the variations from repeated cross-section in the occupation group and location. Each subpanel refers to a different occupation group.

In both samples, OLS results indicate very small, slightly positive coefficients, which are most of the time statistically insignificant. On the other hand, 2SLS models indicate that there is clear evidence that immigration is correlated with a decrease in average routine intensity for native workers. Quantitatively, we find that an increase of 10 p.p. of the immigrant ratio lowers the average routine to abstract intensity by 7.9 p.p. and 3.9 p.p. for respectively workers initially in the tradable and non-tradable sector. In contrast, for construction workers, there is no evidence of a correlation between immigration and the change in routine intensity levels: the coefficient is much lower than for other groups and is not statistically significant.

We also find very little difference between estimates including and excluding location-movers in column 1 and 2. We also observe no effect of a much smaller effect when we concentrate on those who stay in the same occupation group during both periods in Column 3. Note that by definition these workers can only have moved to an occupation within the blue collar worker group. The coefficient is also small and not statistically significant for most occupation group with the cross-section sample. These results imply that most of the effect is driven by workers who have moved to an occupation outside of their initial occupation group.

Is there Positive or Negative selection in Change in Location or Occupation?

We now investigate how individuals changing occupation or location are selected with respect to the sending population. To do so, we first estimate the residual wage dispersion within occupation group and locations by regressing the individual log daily wages for each occupation group in each year against commuting zone fixed effects and on a full set of age fixed effects. By using a residual wage dispersion with respect to the sending population, we investigate whether those who have moved or those who have left had lower or higher wages than those who had stayed with respect to the wage distribution in the initial period. Then, following Borjas (1999), we define positive selection for occupation group k initially in location l in period $t+1$ as a situation in which:

$$E(\log rw_{iklt} \mid \text{movers in t+1}) > E(\log rw_{iklt} \mid \text{stayers in t+1})$$

where rw_{iklt} is the residual wage level in the original location in the initial period. If there is positive (resp. negative) selection, emigrants are on average more (resp. less) productive than non-migrants with respect to the distribution of wages in the initial location. To investigate these selection patterns, we first run the following regressions at the individual level:

$$Move_{iklt+1} = \Gamma_k^1 rw_{iklt} + \Gamma_k^2 (rw_{iklt} \times \Delta p_{lt}) + \beta_k \Delta p_{lt} + \nu_k \Delta Z_{lt} + \phi_k \Delta X_{klt} + \gamma_{kt} + \gamma_{kr} + \epsilon_{klt}$$

where the dependent variable $Move_{iklt+1}$ takes the value 1 if the individual has left the location in period t+1. The coefficients of interest are Γ_k^1 and Γ_k^2, respectively the coefficients of the residual wage in the initial period and of an interaction term between the change in immigrant ratio and the initial residual wage. The first coefficient indicates whether those who had moved to another commuting zone had lower or larger relative wage with respect to the initial wage distribution in the group in their initial location. The second coefficient tests for a potential interaction between the selection term and inflows of immigrants in the location. Estimation is based on 2SLS using the previously described instrument for Δp_{lt} and the interaction of this instrument with the residual wage for the interaction term $\left(rw_{iklt} \times \Delta p_{lt}\right)$.

Results are presented in Panel A of Table 6. Column 1 shows that movers in the occupation group of blue collar workers are negatively selected. Parameter estimates indicate that an increase of one standard deviation of the residual wage (about 0.32), decreases the probability to change location by 3.7 p.p. (0.32 x 0.117). In Column 2, we introduce an interaction term between the residual wage and the share of immigrant inflows. The term is small and statistically insignificant. This suggests that there is no evidence that negative selection varies in places receiving more or less immigrants. Other columns show similar estimates for other occupation groups: for all groups, we also find a negative selection with respect to the sending population and no effect of immigrant inflows on the selection patterns.

In Panel B, we estimate a similar model but in which the dependent variable is the change in routine task intensity in the occupation between period t+1 and t for a given worker. In order to guarantee that the variations in occupations come from individuals experiencing the immigrant inflows and thus who have stayed in the location, we focus on location stayers in this sample. Across occupation groups, we obtain a negative coefficient of the residual wage: this implies that individuals with higher initial wages are more likely to experience a decrease in their routine intensity during the period. Thus, individuals moving to occupations with more abstract tasks and less routine tasks are positively selected. As previously, the interaction term is not statistically significant which implies there is no strong evidence that the selection pattern varies widely depending on immigrant inflows received by the location.[25]

Overall, the results presented in this section confirm the intuition from previous work that changes in locations and occupations are endogenously related to immigrant inflows. Especially important is the fact that the impact differs across occupation groups, with no evidence of an impact of immigration on occupations and larger displacement effects for construction workers.

By studying the selection patterns of workers, we were also able to highlight that those who changed occupation and location are not a random sample of the initial population: workers who change location tend to be negatively selected and have lower initial wages with respect to the sending population. This implies that the selective exit of workers with lowest initial wage from the location will tend to increase wages in the location in the second period. In

[25] We explored more flexible specifications to estimate the interaction term and also estimated the previous models using OLS. The results were broadly similar and are available upon request.

contrast, workers who move to occupations with less routine tasks tend to have higher initial wages and thus tend to be positively selected. This outflow of workers with higher initial wage to other occupations will tend to decrease wages within the occupation group.

IV) The Effect of Immigration on Labor Market Outcomes

Next, we study the impact of immigration on the wages and employment of natives. We have provided in the previous section evidence of selective mobility of natives across locations and occupations in response to immigrant inflows. To assess how this endogenous mobility affects the estimated wage impact of immigration, we estimate four alternative models which differ with respect to their inclusion rule in the final period. First, we address concerns about sample selection in our group of location stayers by carrying an intention-to-treat analysis. In this specification, we include movers in the sample but assign them the immigrant inflow into their initial location. Then, we estimate a second model in which individuals who have moved from the location are excluded. This ensures that our identifying variation in this second model arises from changes in immigrant inflows for stayers. A comparison between these two estimates will indicate how much including stayers in the sample affects the results.

A third model is estimated by further restricting the sample to those who remained in the same occupation group and location during both periods. Finally, we estimate a fourth model using repeated cross-section of workers in the occupation group across locations. Workers in the cross-section sample in the initial period are the same as in the balanced sample, but they differ in the second period given some workers have left and new workers have entered the occupation group in the location.[26]

Differences across the estimated models arise through the sorting of individuals across locations and occupations. A comparison of these estimates will thus indicate how much self-

[26] To keep the results comparable, as in the balanced sample, we also focus on the observed change in outcomes for workers aged 25-45 in the initial period and 35-55 in the end period.

selection into occupations and location affects the measured impact of immigration on wages. If changes in occupation and location are not important at the aggregate level, we should find little differences across models. Instead, if compositional changes are correlated with immigrant inflows, the estimates should differ.

Effect on the number of days worked

We start by estimating the effect of immigration on the number of days worked. To do so, we use as a dependent variable the relative change in the number of days worked $\frac{D_{kt+1} - D_{kt}}{D_{kt}}$ where D_{kt} is the average number of days worked by group k in period t.[27]

The first column in each subpanel of Table 7 presents regression results using a balanced sample of natives defined by their initial occupation. Overall, we find no evidence of a correlation between the change in the average number of days worked and an increase in the share of low-educated migrants. The coefficients of 2SLS models are sometimes negative but relatively small in most specifications. A notable fact is that we find larger coefficients in the construction sector: for this group, the estimates suggest that an increase of 10 p.p. of the immigration rate would decrease by 2% of the average number of days worked. However, the point estimates are very imprecise and are not statistically different from zero.

A potential risk for the validity of our results is attrition. One drawback of the previous measure of number of days worked is that individuals supplying zero days of work are excluded from the DADS sample. Our estimates might thus be affected by a selection bias if some natives do not work during a year as a result of immigration. To address this limitation, panel A in Table 8 uses data from a balanced sample of workers in which zero days of work have been imputed to individuals who are not in the sample in period $t+1$. These estimates

[27] Results are identical if one uses changes in the log of the average number of days worked in the cell.

correct for the effect of non-participation in period t+1 under the strong assumption that all individuals not observed in the sample have been out of the labor force during the year. Once again, we do not find a negative impact of immigration in these specifications. If anything, 2SLS models report a positive correlation which is inconsistent with the hypothesis that immigration might decrease the number of days worked of natives.

The previous estimates should be interpreted with caution given there are some doubts about the quality of the variable on the number of days worked available in the DADS. For this reason, Panel B in Table 8 reports estimates of the impact of changes in the proportion of immigrants on the employment to population rate using Census data. As in the previous section, we estimate separate models for various groups of natives defined by their education level.[28] The general pattern is very similar: changes in immigrant rates do not appear to be correlated with a decline in employment rate for prime-age male workers from different education groups. Parameter estimates are always small, and most of the time statistically insignificant.[29]

Effect on wages

We next estimate the effect of immigration on wages. We focus on changes in the median annual log wage for full time workers in a given occupation group. Using the median annual wage has the advantage of providing estimates relatively insensitive to the presence of outliers and, in addition, enables a series of robustness checks related to attrition that we present below. We also explore other options below, however, with specifications that use median daily wages and average daily wages.

[28] Notice that we follow the same sample requirement, and use the change in employment rate of male aged 25-45 in period t and male aged 35-55 in period t+1.

[29] We have also estimated similar model by using the initial location of a worker to calculate the employment rates, thus making an “intend to treat” estimate. We also found no effects.

The relationship between changes in median annual log wages and immigrant inflows is examined in Table 9. The OLS coefficients for most groups are rather small, positive and non- significant in most specifications. In contrast, endogeneity-corrected parameter estimates significantly differ across occupations. Point estimates are negative, relatively large and statistically significant. Results with the balanced sample including location-movers indicate that an increase of 10 p.p. in the share of low-educated immigrants lowers the median log annual wage by -1.3% for workers initially blue collar in the non-tradable sector. For workers in the tradable sector, the coefficient is also negative and has the same magnitude but is not statistically significant. The impact of immigration also appears to be quite heterogeneous across occupation groups: the results show larger effects for workers in the non-tradable sector and particularly those in the construction sector. In the construction sector, the estimates indicate that a 10 p.p. increase predicts a decrease of the median wage by 3.6 p.p. Qualitatively, these estimates are in line with Bratsberg and Raaum (2012) who report that an increase in 10 p.p. in the immigration ratio is accompanied by a 6 p.p. fall in the wages of construction workers.

A comparison between Columns 2 and 3 within each panel indicates the extent to which location and occupation stayers are a selected sample. The estimates present a contrasting pattern: the estimates in Column 2 where location-movers have been excluded are quite close for blue collar workers or lower for construction workers but they are slightly larger for workers in the non-tradable sector. Overall, differences between models including or excluding location-movers are relatively small for most groups.

In Column 3, where the sample excludes those who are not in the same occupation group in the second period, the coefficients are unambiguously larger for most groups. The estimates indicate that an increase of 10 p.p. of the immigration rate predicts a decrease of median wage of 1.3 p.p. for blue collar, 1.7 p.p. for the non-tradable sector and 4.8 p.p. for the construction sector.

Finally, results in Column 4 are based on the cross-sectional variation of wages within occupations. The impact of immigration is substantially larger in cross-section estimates except for the construction sector. With respect to estimates using the balanced sample, the estimated coefficient is multiplied by two for blue collar workers and non-tradable sector workers.

There are two main lessons from the previous results. First, the findings described above point to a strong heterogeneity in the estimated effect of immigration across workers depending on their initial occupation. Unsurprisingly, the estimates are much larger for workers initially in the non-tradable sector and in the construction sector.

Second, we find a much larger effect of immigration on those who stay in the skill group during both periods which implies that occupational mobility mitigates the impact of immigration, particularly for workers who are initially in the construction sector. This suggests that immigration affects to a larger extent the average wages in given occupations than the wages of workers initially in those occupations. Instead, estimates including or excluding location-movers are basically equivalent, which shows that geographical mobility does not seem to play an important role in mitigating the impact of immigration.

Robustness

Table 10 examines the sensitivity of the results to the specification of the baseline model. We examine in Panel 1 the robustness of estimates using the balanced panel while Panel 2 reports cross-section estimates. We concentrate on the impact of immigration on wages and we focus on blue collar workers and those in the non-tradable and in the construction sector. We focus on 2SLS estimates to save space (OLS results are available upon request).

We first examine the results for the balanced panel in Panel 1. One issue with our instruments might be that the lagged distribution of immigrants is correlated with persistent trends in economic dynamism across locations. As a result, the exclusion restriction of our estimates might not be perfectly valid. A simple way to test this hypothesis is to estimate whether the estimates change when we exclude different sets of control variables.[30] If the estimates change significantly, this would indicate that the immigrant inflows predicted by our instrument are strongly correlated with other factors influencing wages across locations. Rows 1, 2 and 3 examine the sensitivity of the previous estimates to the inclusion of an increasingly detailed set of control variables. A comparison between regression results in row 1 which do not includes controls (except for time dummies) and row 2 suggests that results are barely affected by the inclusion of additional covariates. There is also very little change to the coefficients from adding regional trends (row 3). Overall, these patterns are not consistent with the hypothesis that our instrument might be correlated with unobserved determinants of wage changes across locations.

An additional test for the validity of our instrumental variable strategy is provided by using more distant lags to compute the instrument. To do so, we construct an alternative instrument using the distribution of immigrant communities corresponding to two censuses before.[31] By increasing the distance between the initial distribution of immigrants across locations used to compute the shift share and the change in the immigrant ratio predicted by the shift share, we are more likely to purge the instrument for potential persistent correlations with unobserved local trends. Row 4 provides results using this alternative instrument. As

[30] Another good reason to exclude the set of location specific control variables is that these controls might be endogenous. This would be the case for example if variables such as the share of workers in the construction sector or in the manufacturing sector are significantly affected by immigrant inflows.

[31] Attempts to use very distant lags such as predicting changes from 1975 to 2007 by using only the 1968 distribution failed because they are too weakly correlated with changes which occurred during the 1990s and the 2000s. This is due to the fact that more than half low-educated migrants who arrived after 1980 come from Asia and South-Africa and these groups were quasi-absent from France before 1975.

previously, we obtain negative coefficients which are statistically significant. However, these coefficients are also smaller by a third for blue-collar workers and workers in the non-tradable sector.

The analysis so far has been based on changes in median annual log wages. We now explore the sensitivity of the results to the definition of the dependent variable. Row 5 uses the log of the median *daily* wages in the cell instead as a dependent variable. The estimated effects are somewhat lower, particularly for workers in the construction sector. Row 6 shows results using average daily wages. The estimated coefficient is strikingly similar than those obtained with median daily wages for blue collar workers and is larger for workers in the non-tradable sector. In contrast, the estimated impact on construction workers diminishes widely and becomes insignificant. We suspect this last result reflects the fact that a relatively larger share of construction workers has several employers in a given year. This implies that there might be much more measurement errors in the number of days worked for this group when daily wages are used.

In Rows 7 and 8, we investigate the extent to which the results might be driven by large locations such as Paris, Marseilles or Lyons, which attract a disproportionately large share of immigrants. Row 7 presents estimates where the 30 largest commuting zones have been excluded from the sample while row 8 reports unweighted regressions. Results are broadly similar in these two models.

The final specification check in Row 9 is oriented towards addressing a number of concerns related to attrition. Using median wages in the cell enables us to investigate the sensitivity of the results to missing wage information by using simple imputation techniques as in Neal and Johnson (1996) or Olivetti and Petrongolo (2008). Specifically, we investigate how our results depend on including individuals with a missing wage observation in period $t+1$ in the sample under the assumption that all missing individuals are out of the labor force and are thus earning a log wage of zero. Results of this exercise in Row 9 indicate our estimates are reasonably robust. We also obtain a similar ranking across occupations, point estimates being slightly larger for workers from non-tradable industries and lower for the blue collar group.[32]

Panel B reports the same robustness tests performed using the cross-section sample. We also find the baseline results to be reasonably robust across most specifications but the precision of the estimates diminishes in some specifications. Importantly, the estimates are not statistically significant when the alternative instrument using lagged settlement patterns of immigrants in used. Another noteworthy pattern is that unweighted specifications provide much larger parameter estimates.

V) Discussion

In this paper, we have revisited the impact of immigration on the labor market outcomes of natives. Unlike most of the previous literature, our rich dataset has provided us with a unique opportunity to investigate heterogeneity in the impact of immigration while controlling for composition effects. Specifically, we have tested whether the impact of low-educated immigration differed across natives using homogenous groups defined by their initial occupation. We have also controlled for changes in the composition of the labor force at the local level by focusing on estimates using variations over time from a balanced sample.

First, our findings show that immigrant inflows are moderately correlated with both native outflows and inflows, and with a reallocation of natives to occupations with less routine tasks. Our results also point to the evidence that the correlation between immigrant inflows mobility across locations and occupations varies strongly depending on the industry of origin.

[32] We have also evaluated the risk of attrition from a selective shift of some workers to a sector uncovered by the DADS panel such as the public sector which is only partially covered by the DADS before 1990. We found basically no correlations between changes in the share of government employees and a change in the share of migrants. These results are available upon request.

Moreover, we find that location and occupation-movers are a selected subgroup of the sending population. While location-movers tend to be negatively selected from the sending population, those moving to occupations with less routine tasks tend to be positively selected. This implies that the selection patterns related to changes in location and occupation strongly differ.

Empirically, we do not find strong evidence that the selection of natives across locations affects importantly the estimates of the impact of immigration. On the other hand, the endogenous selection of natives towards occupations requiring different skills decreases significantly the impact of immigration on wages. We obtain a much larger impact of immigrant inflows on wages on the selected subgroups of natives who do not change location and stay in the same occupation group in both periods.

Importantly, our results point to a strong heterogeneity across occupation groups in the impact of immigration. We find that the wages of blue collar workers initially in the tradable sector are the less affected by immigrant inflows while the effect of immigration on changes in occupations are found stronger for this group. In contrast, for the group of construction workers, we find a much larger impact of immigration on wages but no correlation between immigrant inflows and change in occupations for this group. This last result suggests that part of the difference in the impact of immigration on wages across occupation groups might reflect the fact that workers in some occupation groups are more able than others to protect themselves from immigrant inflows by shifting occupation.

Our results have important implications for the analysis of the impact of immigration. First, the results suggest that the wage impact of immigration varies across occupation groups and individuals both because labor markets are segmented and also because natives between and within groups react differently to immigrant inflows. Second, the fact that immigrant inflows are correlated with native mobility across location and occupation groups complicates the estimates of the impact of immigration. Native mobility responses imply that immigration affects indirectly other locations and occupation groups.

There are however several limitations to the previous results. First, because we wanted to minimize the risk that our results might be biased by non-participation which is not well captured in our data, we have focused on prime aged male workers. According to recent work from Smith (2012), immigrants might also be more in competition with young workers less than 25 that were not included in our analysis. Another limitation is that we did not include women in our analysis given that the treatment of labor market participation creates an additional complexity for this group. Finally, the share of immigrants and natives in the service sector is also rapidly growing while the share of blue collar workers is in constant decline. An evaluation of the impact of immigration on this increasingly important segment of the labor market would be of substantial interest for future work.

Appendix

Data appendix

Occupations: DADS data contains information on occupation for CSP with 27 categories before 1983 and 36 categories afterward. The category "*Blue collar workers*" aggregates 6 distinct sub-occupations over the period. We merge these occupations with tasks intensity indexes by Goos et al. (2010, Table 4 p.49) based on the Occupational Information Network (ONET) database.

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 the DADS until 1993. We have created crosswalk tables with other industry classifications to match them with the NAP at the four digit level. The NAF (*Nomenclature d'Activité Française*) is used in the 1999 Census and in the DADS from 1993 to 2002. For the match between NAP and NAF, we have used the 1994 LFS (*Enquête emploi*) 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.

Education The education variable reported in the Census indicates the diploma received by the individual. We use the variable *DIP* in the 1968, 1975 and 1982 censuses, *DIPL1* in the 1990 Census and *DIPL* in the 1999 Census. We classify individuals in four groups: 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. 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 or a BEP. High school education includes individuals who have a diploma equivalent to the Baccalaureate. This group also includes general, professional or technical Baccalaureate graduates. College level includes all individuals with a diploma of a level superior to the Baccalaureate.

Theoretical Appendix

The model is a straightforward adaptation of Combes et al. (2008) and Combes et al. (2012) which was initially used to investigate the sorting of workers with different skill levels across local labor markets. We also follow Card (2001) and make the assumption that local labor markets are stratified along "skill" group lines. For the moment, we abstract from labor supply decisions and assume that each worker provides one unit of labor. This implies that local labor supply is only determined by workers' location decisions. The profit of the representative firm in location l, and year t is given by:

$$\pi_{lt} = p_{lt} y_{lt} - \sum_{i \in lt} w_{it} l_{it} - r_{lt} z_{lt}$$

In this expression, p_{lt} is the local price of output y_{lt}. For any worker i, w_{it} is the wage rate and l_{it} is the total labor supply from workers of this type. Other factors of production are represented by z_{lt} and r_{lt} is their price. The production function of the firm is:

$$y_{lt} = A_{lt} L_{lt}^{b} z_{lt}^{1-b}$$

where $0 < b \leq 1$, A_{lt} is the total factor productivity in the area. We assume L_{lt} is a CES aggregate of the labor inputs of workers from different occupation groups. As in Combes et al. (2008), to introduce heterogeneity within occupation groups, we assume individuals in a given occupation group are perfect substitute but supply different efficiency units of labor. This implies that:

$$L_{lt} = \left[\sum_{k} L_{klt}^{(\sigma-1)/\sigma} \right]^{\sigma/\sigma-1} = \left[\sum_{k} \left(\sum_{i \in klt} s_{it} l_{it} \right)^{(\sigma-1)/\sigma} \right]^{\sigma/\sigma-1}$$

where σ determines the elasticity of substitution between labor types. The level of skills s_{it} augments the effective units of labor supplied by a given individual, thereby making workers more productive. At competitive equilibrium, profit maximization implies:

$$w_{it}(k,l) = B_{lt} s_{it} L_{klt}^{-1/\sigma}$$

where $B_{lt} = b(1-b)^{\frac{1-b}{b}} \left(p_{lt} A_{lt} r_{lt}^{-(1-b)} \right)^{\frac{1}{b}} L_{lt}^{1/(\sigma-1)}$. To take the model to the data, we assume that for workers of type i : $\log s_{it} = X_{it}\phi + \alpha_i$, where X_{it} is a vector of time-varying observed characteristics of the worker and α_i is a worker fixed effect unobserved productivity.

Firms can employ native labor N_{klt} or immigrant labor I_{lt}, we assume that immigrant and native labor of the same type are perfect substitute. Labor supply in an occupation group can thus be decomposed by the efficiency units supplied by natives and low-educated immigrants. Finally, using the following approximation, $\log L_{klt} \approx \log N_{klt} + \gamma_k \frac{I_{lt}}{N_{klt}}$, it is straightforward to obtain Eq. (1).

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Table 1 : Share of Foreign born Workers among blue collar workers across Selected Industries and Regions in France in 1999

Industry	Share of foreign born workers				Share total Employment
	France	Paris	Lyons	Brittany	
Non-Tradable	14.5	62.0	16.2	3.4	62.0
Tradable	10.6	31.1	15.7	1.9	31.1
Construction	20.2	16.4	23.9	5.0	16.4

Source: Panel DADS. All figures refer to blue collar workers only. Paris and Lyons regions refer respectively to the region "*Ile de France*" and "*Rhone-Alpes*".

Table 2: Share of Foreign Born among Construction Workers in the Paris and Brittany regions, 1976-2007

	1976	***1982***	***1990***	***1999***	***2007***
Paris	37.2	37.1	35.6	45.7	41.7
Brittany	3.8	4.2	4	5.0	6.9

Source: Panel DADS. All figures refer to blue collar workers.

Table 3: First Stage Results

Dependent variable : *Change in Low-Educated Immigrant Ratio* Δp_{lt}			
	(1)	(2)	(3)
Predicted change	0.166***	0.121***	0.091***
	(0.051)	(0.028)	(0.027)
F-stat	10.54	17.74	10.97
R-squared	0.13	0.33	0.29
Additional Controls	No	Yes	Yes
Weight	Yes	Yes	No

Note: All regressions use 1188 observations and include a full set of regions and time fixed effects. Additional controls included in the regressions when indicated. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$ except when indicated otherwise. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 4: Impact of Low-Educated Immigration on Native inflows and outflows at the Commuting Zone Level

1. DADS Data				
Sample: Male workers 25-45 in *t*, 35-55 in $t+1$, initially working in industry.				
	All Blue Collar	Tradable	Non-tradable	Construction
	A. Dependent variable: *Outflows between t/t+1*			
	OLS			
Δp_{lt}	0.070***	0.046	0.089***	0.090***
	(0.024)	(0.028)	(0.030)	(0.030)
	2SLS			
Δp_{lt}	0.160*	0.005	0.248**	0.358**
	(0.091)	(0.118)	(0.122)	(0.154)
	B. Dependent variable: *Inflows between t/t+1*			
	OLS			
Δp_{lt}	0.160***	0.156***	0.164***	0.173***
	(0.031)	(0.039)	(0.036)	(0.050)
	2SLS			
Δp_{lt}	0.147	0.165	0.144	0.158
	(0.104)	(0.114)	(0.138)	(0.169)
2. Census Data				
	Primary Education	Secondary Education	High-School	University
	A. Dependent variable: *Outflows between t/t+1*			
	OLS			
Δp_{lt}	0.044***	0.043**	-0.029	-0.027
	(0.014)	(0.019)	(0.021)	(0.029)
	2SLS			
Δp_{lt}	0.238**	0.274**	0.238	0.125
	(0.096)	(0.131)	(0.178)	(0.202)
	B. Dependent variable: *Inflows between t/t+1*			
	OLS			
Δp_{lt}	0.110***	0.137**	0.104	0.104
	(0.041)	(0.057)	(0.074)	(0.109)
	2SLS			
Δp_{lt}	0.222	0.258	0.456	0.560
	(0.176)	(0.230)	(0.357)	(0.514)

Note: All regressions use 1188 observations and include a full set of regions and time fixed effects. Additional controls included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 5: Impact of Immigration on Occupation Characteristics

A. Dependent variable : change in average routine task t/t+1 Sample: Male 25-45 in t+1, 35-55 in t								
	Blue Collar				Tradable			
	Balanced sample	Location Stayer	Location & Occupation Stayer	Cross-Section	Balanced sample	Location Stayer	Location & Occupation Stayer	Cross-Section
	OLS							
Δp_{lt}	0.03	0.023	0.017	0.010	0.003	0.000	0.028**	0.025**
	(0.039	(0.050)	(0.012)	(0.013)	(0.054)	(0.069)	(0.014)	(0.011)
	2SLS							
Δp_{lt}	-0.623***	-0.653***	-0.147**	-0.049	-0.791***	-0.703**	-0.137*	-0.199**
	(0.184)	(0.199)	(0.072)	(0.079)	(0.270)	(0.245)	(0.075)	(0.090)
	Non-tradable				Construction			
	OLS							
Δp_{lt}	0.052	0.053	-0.001	0.005	0.028	0.008	-0.020*	-0.016
	(0.040)	(0.054)	(0.014)	(0.013)	(0.039)	(0.053)	(0.012)	(0.012)
	2SLS							
Δp_{lt}	-0.388**	-0.434**	-0.041	0.051	-0.181	-0.370	-0.02	-0.011
	(0.168)	(0.214)	(0.080)	(0.092)	(0.197)	(0.293)	(0.082)	(0.063)

Note: All regressions use 1188 observations and include a full set of regions and time fixed effects. Additional controls are included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt} + 1/N_{klt-1})^{-1/2}$. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 6: Selection Patterns of Location and Occupation-Movers: Individual Level Evidence

A. Dependent Variable: Moved to another Location								
	Blue Collar		Tradable		Non-Tradable		Construction	
Residual Wage	-0.117	-0.119	-0.089	-0.081	-0.098	-0.105	-0.094	-0.116
	(0.003)	(0.006)	(0.007)	(0.017)	(0.003)	(0.007)	(0.007)	(0.018)
RW x Δp_{lt}		0.018		-0.114		0.101		0.287
		(0.085)		(0.224)		(0.116)		(0.297)
Δp_{lt}	0.258	0.257	0.263	0.264	0.249	0.245	0.545	0.518
	(0.091)	(0.094)	(0.115)	(0.118)	(0.095)	(0.098)	(0.116)	(0.121)
N	345 414	345 414	157 569	157 569	187 841	187 841	60 609	60 609
B. Dependent variable: Change in routine to abstract task intensity, excludes location-movers								
Residual Wage	-0.355	-0.361	-0.578	-0.585	-0.232	-0.227	-0.315	-0.345
	(0.010)	(0.017)	(0.019)	(0.039)	(0.011)	(0.014)	(0.018)	(0.055)
RW x Δp_{lt}		0.090		0.118		-0.077		0.436
		(0.195)		(0.477)		(0.240)		(0.821)
Δp_{lt}	-0.502	-0.507	-0.369	-0.372	-0.377	-0.373	-0.455	-0.488
	(0.182)	(0.187)	(0.153)	(0.154)	(0.173)	(0.180)	(0.367)	(0.351)
N	275 854	275 854	134 977	134 977	140 705	140 705	46 945	46 945

Note: All regressions include a full set of regions and time fixed effects. Additional controls are included in the regressions. Standard errors are clustered at the regional level. All models are estimated with 2SLS.

Table 7: Impact of immigration on Number of Days Worked

Dependent variable : change in average number of days worked t/t+1 Sample: Male 25-45 in t, 35-55 in t+1								
	Blue Collar				Tradable			
	Balanced sample	Location Stayer	Location & Occupation Stayer	Cross-Section	Balanced sample	Location Stayer	Location & Occupation Stayer	Cross-Section
	OLS							
Δp_{lt}	0.007	-0.003	-0.002	0.009	0.001	0.009	-0.000	0.019
	(0.007)	(0.006)	(0.006)	(0.010)	(0.008)	(0.012)	(0.008)	(0.012)
	2SLS							
Δp_{lt}	0.013	-0.003	-0.015	-0.079	0.052	0.061	0.041	-0.047
	(0.034)	(0.027)	(0.035)	(0.068)	(0.042)	(0.062)	(0.051)	(0.073)
	Non-tradable				Construction			
	OLS							
Δp_{lt}	0.011	-0.009	-0.010	-0.003	0.003	0.031	-0.013	0.000
	(0.010)	(0.009)	(0.009)	(0.012)	(0.013)	(0.027)	(0.011)	(0.016)
	2SLS							
Δp_{lt}	0.011	-0.042	-0.024	-0.083	-0.148	-0.267	-0.232	-0.214
	(0.010)	(0.042)	(0.055)	(0.085)	(0.105)	(0.178)	(0.211)	(0.151)

Note: All regressions use 1188 observations and include a full set of regions and time fixed effects. Additional controls are also included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 8: Additional Evidence on the Impact of Immigration on Number of Days Worked

	Dependent variable: change in average number of days worked t/t+1 Sample definition: Male 25-45 in t, 35-55 in t+1			
	A. Balanced Sample : Zero imputed if missing in t+1			
	Blue Collar	Tradable	Non-Tradable	Construction
	OLS			
Δp_{lt}	-0.037	-0.035	-0.044	-0.027
	(0.023)	(0.021)	(0.027)	(0.028)
	2SLS			
Δp_{lt}	0.328**	0.329	0.219*	0.280*
	(0.148)	(0.196)	(0.124)	(0.165)
	B. Census Data Evidence: *Dependent Variable: Change in Employment/Population Rate t/t+1*			
	Primary Education	Secondary Education	High-School	University Graduates
	OLS			
Δp_{lt}	0.026**	0.009*	0.003	-0.001
	(0.011)	(0.005)	(0.008)	(0.046)
	2SLS			
Δp_{lt}	-0.074	0.004	-0.031	-0.030
	(0.095)	(0.047)	(0.046)	(0.046)

Note: All regressions use 1188 observations and include a full set of regions and time fixed effects. Additional controls are also included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt} + 1/N_{klt-1})^{-1/2}$. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 9: Impact of Immigration on Median Annual Wages

Dependent variable : change in median annual wage t/t+1 Sample: Male 25-45 in t+1, 35-55 in t								
	Blue Collar				Tradable			
	Balanced sample	Location Stayer	Location & Occupation Stayer	Cross-Section	Balanced sample	Location Stayer	Location & Occupation Stayer	Cross-Section
	OLS							
Δp_{lt}	0.015	0.016	0.030	0.042**	0.012	0.035	0.012	0.059**
	(0.013)	(0.013)	(0.012)	(0.019)	(0.017)	(0.022)	(0.016)	(0.023)
	2SLS							
Δp_{lt}	-0.131**	-0.107*	-0.130*	-0.285*	-0.126	0.039	-0.185**	-0.235
	(0.057)	(0.060)	(0.073)	(0.163)	(0.086)	(0.100)	(0.087)	(0.166)
	Non-tradable				Construction			
	OLS							
Δp_{lt}	0.008	0.016	0.019	0.007	0.022	0.031	0.015	0.027
	(0.019)	(0.016)	(0.016)	(0.020)	(0.024)	(0.026)	(0.029)	(0.025)
	2SLS							
Δp_{lt}	-0.133**	-0.162*	-0.171*	-0.361**	-0.367**	-0.267*	-0.479**	-0.467**
	(0.065)	(0.087)	(0.095	(0.166	(0.17	(0.154)	(0.240)	(0.199)

Note: All regressions use 1188 observations and include a full set of regions and time fixed effects. Additional controls are included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt} + 1/N_{klt-1})^{-1/2}$ where N_{klt} represents the size of the occupation group k in location l and year t. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 10: Sensitivity of the Effects of Immigration on Median wages to alternative specifications

	Blue Collar	Non-tradable	Construction	N
A. Balanced Panel				
1. No covariates	-0.178***	-0.177**	-0.354**	1188
	(0.069)	(0.081)	(0.153)	
2. Covariates	-0.177**	-0.174**	-0.331**	1188
	(0.072)	(0.081)	(0.153)	
3. Only Region FE	-0.139**	-0.154*	-0.416**	1188
	(0.058)	(0.087)	(0.152)	
4. Instrument lagged	-0.094**	-0.091*	-0.366**	1188
	(0.042)	(0.054)	(0.106)	
5. Dependent variable:	-0.170***	-0.112*	-0.206**	1188
Median daily wage	(0.063)	(0.060)	(0.130)	
6. Dependent variable:	-0.170**	-0.223**	-0.077	1188
Average daily wage	(0.080)	(0.103)	(0.189)	
7. Exclude largest cities	-0.178**	-0.141	-0.419*	1064
	(0.090)	(0.127)	(0.255)	
8. Without weights	-0.212**	-0.155	-0.399*	1188
	(0.109)	(0.106)	(0.222)	
9. Log wage of	-0.095*	-0.195**	-0.351**	1188
zero imputed if missing in t+1	(0.055)	(0.091)	(0.179)	
B. Repeated Cross-section				
1. No covariates	-0.221	-0.243*	-0.378*	1188
	(0.133)	(0.146)	(0.201)	
2. Covariates	-0.212	-0.246*	-0.388*	1188
	(0.135)	(0.149)	(0.210)	
3. Only Region FE	-0.283*	-0.374**	-0.467**	1188
	(0.161)	(0.166)	(0.196)	
4. Instrument lagged	-0.092	-0.108	-0.116	1188
	(0.080)	(0.093)	(0.103)	
5. Dependent variable:	-0.135*	-0.154*	-0.178	1188
Median daily wage	(0.079)	(0.080)	(0.144)	
6. Dependent variable:	-0.121	-0.195	-0.295	1188
Average daily wage	(0.108)	(0.132)	(0.196)	
7. Exclude largest cities	-0.426	-0.459*	-0.519*	1067
	(0.276)	(0.264)	(0.307)	
8. Without weights	-0.670*	-0.579**	-0.483**	1188
	(0.397)	(0.282)	(0.221)	

Note: See Table 9.