WHO STAYS AND WHO LEAVES? IMMIGRATION AND THE SELECTION OF NATIVES ACROSS LOCATIONS

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ABSTRACT

We study the impact of local immigration inflows on natives' wages using a large French administrative panel from 1976-2007. We show that local immigration inflows are followed by reallocations of blue-collar natives across commuting zones. Because these reallocations vary with the initial occupation and blue-collar location movers have wages below the blue-collar average, controlling for changes in local composition is crucial to assess how wages adjust to immigration. Immigration temporarily lowers the wages of blue-collar workers, with unskilled workers experiencing larger losses. Location movers lose more than stayers in terms of daily wages but move to locations with cheaper housing.

KEYWORDS
Immigration, Wages, Employment, France.

JEL

J15, J31.

Who stays and who leaves? Immigration and the selection of natives across locations[1]

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Abstract

We study the impact of local immigration inflows on natives' wages using a large French administrative panel from 1976-2007. We show that local immigration inflows are followed by reallocations of blue-collar natives across commuting zones. Because these reallocations vary with the initial occupation and blue-collar location movers have wages below the blue-collar average, controlling for changes in local composition is crucial to assess how wages adjust to immigration. Immigration temporarily lowers the wages of blue-collar workers, with unskilled workers experiencing larger losses. Location movers lose more than stayers in terms of daily wages but move to locations with cheaper housing.

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Introduction

When migrant workers are substitutes to native workers, an increase in local labor supply induced by immigration should lower the wages of competing native workers in the short run. However, immigration inflows may also generate a geographical reallocation of natives, which attenuates the local impact of immigration on wages and spreads the effects of immigration to other locations (Borjas, Freeman, et Katz 1997). Another consequence less studied in the literature is that those who move might be systematically different from those who stay. We show in this paper that when movers and stayers are different, and reallocation is important, such selective mobility masks the causal negative effect of immigration on local wages when longitudinal data are not available to take this selection into account.

To guide our empirical investigation, we start by describing a simple Roy model à la Gibbons, Katz, Lemieux, and Parent (2005). In the model, an inflow of immigrants into a location affects relative wages across locations, thus generating incentives for reallocation. As returns to ability vary across locations, high (low)-ability natives relocate to areas where ability matters more (less). This implies that when reallocations are important, local changes in average wages reflect not only the effect of immigration on wages but also changes in average ability across locations. These simultaneous changes make it difficult to empirically distinguish the impact of immigration on wages from its effects on the composition of workers.

To test the empirical relevance of these hypotheses, our study uses a large administrative French panel from 1976 to 2007 that provides exhaustive and reliable information on the wages, occupations and geographical locations at the commuting zone level for approximately 4% of all French private sector employees. As the data do not include long-term unemployed of more than a year, our analysis focuses on prime-aged males 25-59, who are the most attached to the labor market. We also rely on very large (25%) sample extracts from the French Census to precisely count the number of immigrants in each commuting zone and to construct an instrumental variable for their inflows based on ethnic networks.

We use our large administrative panel to follow workers over time and to neutralize any compositional changes that follow immigrant inflows. In contrast to existing studies—generally based on average changes across local labor markets captured in cross-sectional data (see e.g. Altonji et Card 1991)— we estimate the effects of an increase in labor supply due to immigration on wages using groups of workers defined by their *baseline*, instead of their current, location, and we include in the sample both those who stayed and those who moved from their baseline location after the inflow of immigrants. Such approach maintains constant the sample composition and directly eliminates variations in wages related to endogenous changes in the local composition of the workforce.

We also check whether the impact of immigration depends on the initial occupations of natives, as immigration into France is mainly blue-collar and unskilled. However, to avoid misclassifications stemming from the occupational downgrading of immigrants,[4] we do not allocate immigrants into specific occupation groups but instead estimate separately how each occupation group responds to the overall local immigration shock.

We deal with the endogeneity of immigration with a shift-share instrument (Card 2001; Cortes 2008) that predicts inflows across commuting zones by combining the initial distribution of immigrant communities in 1975 with differences in inflows to these communities at the national level. Whereas important concerns on the use of such instruments have been raised for the U.S. (Jaeger, Ruist, et Stuhler 2018), we document that the shift-share approach appears less problematic for France because the country-of-origin mix of

[4]Cohen-Goldner and Paserman (2011) and Dustmann and Preston (2012) indicate that immigrants "downgrade" at arrival in the sense that they work in jobs of much lower quality than similarly educated natives.

immigrants has dramatically changed over time and local immigrant inflows are less autocorrelated.

We find strong evidence of an impact of immigration on the mobility of natives, and particularly so for blue-collar workers. Specifically, our estimates show that a larger immigration-driven increase in labor supply in a commuting zone is associated with: (i) a higher probability for natives from this location of moving to a job in a different location, and (ii) a lower probability for natives from other locations to move to a job in this location. Movers are not randomly selected as the extent of the above effects varies with the initial occupation of the worker and with his initial wage rank in the occupational distribution. In particular, among skilled blue-collar natives, location leavers are mainly drawn from the bottom of the initial wage distribution, which might mechanically increase the average wage in the location after they have left.

In the second part of the paper, we investigate the extent to which these selective reallocations affect the measurement of the wage impact of immigration. We find that taking into account local changes in the composition of the native workforce is crucial to estimating the wage impact of immigration. Specifically, when using the baseline location to define groups of workers (i.e. when keeping composition constant), a 1 p.p. local inflow of immigrants lowers the average daily wage of natives initially in a skilled blue-collar occupation by approximately 0.33%, and this effect is even stronger (a 0.99% fall in the daily wage) for the unskilled blue-collars. At the same time, the number of days worked by natives—expected to go down if immigration raises their unemployment probability- remains unaffected by immigration when stayers and leavers are pooled in the sample, with the important exception of managers for whom we find evidence of a negative effect of immigration on the annual number of days worked.

We compare these estimates with estimates based on the current location of workers, following the approach in the literature exploiting cross-sectional data. When using current location, our results are dramatically different, as we obtain either positive or much lower and statistically insignificant estimates of the impact of immigration on average wages. This result confirms that the geographical reallocation of natives with lower initial wages conceals part of the negative effect of immigration on wages.

We also explore whether location out-migration enables natives to alleviate the fall in wages generated by immigration, as predicted by the baseline version of our theoretical model. When comparing movers and stayers, we find substantial differences in the impact of immigration on daily wages and number of days worked, and particularly so for blue-collar workers. On the one hand, movers are characterized by larger declines in daily wages than stayers. At the same time, this larger decline in daily wages appears to be compensated for by an increase in the annual numbers of days worked for movers, and overall this translates into an insignificant impact of immigration on annual wages for them.

Differences in the characteristics of their origin and destination commuting zones might also affect the utility of movers. We find that native workers who change commuting zones tend to move to work in locations with lower housing costs. When we adjust wages using a local cost of living index based on local differences in housing costs, the additional daily wage losses of movers become insignificant. However, this result must be interpreted with caution, as we cannot account for all relevant changes in local amenities that affect utility and might be correlated with lower housing costs. In addition, our data only contains detailed information on the location of the job and not on the place of residency, and some of the observed job mobility might reflect changes in commuting patterns instead of residential mobility.

Most of these results are robust to an alternative construction of the instrument or to controls for lagged immigrant inflows. In demanding specifications that include regional or commuting zone fixed effects, our estimates tend to be reasonably robust except for wages, for which the estimates become insignificant.

This paper contributes to the literature in the following ways. First, our work is directly related to Bratsberg and Raaum (2012), who report that selective attrition of native workers in the construction sector in Norway masks the causal wage impact of immigration in that sector. Whereas they focus on the construction sector, we consider here the entire French private sector and document how immigration affects the selection of natives across local labor markets and not just a single sector. In addition, whereas they exclude from their analysis those who left the construction sector, we consider the impact of immigration on both those who stayed and left the locations.[5]

Second, our results confirm that natives' changes in location are important channels of adjustment to immigration, as underlined by Borjas (2006), Wagner (2010), Őzden and Wagner (2014) and Lull (2018) and consistent with the literature on local adjustments to labor demand shocks (Blanchard et Katz 1992; Molloy, Smith, et Wozniak 2011; Amior et Manning 2018). On the other hand, we also find that part of the local adjustment to immigration occurs through a reduction in inflows, as in Dustmann, Schönberg, and Stuhler (2017) or Monras (2018), among others.[6]

The rest of the paper proceeds as follows. Section I proposes a conceptual framework for the study of the geographical reallocation of natives following immigration, which is

[5] Our results on the importance of compositional changes in estimating the effects of immigration are also consistent with recent evidence from Clemens and Hunt (2019) that documents important changes in the composition of the native sample in the CPS data following the Mariel Boatlift.

[6] Relative to earlier work on France, our results differ from Ortega and Verdugo (2014), which reports a positive correlation between immigration and the wages of natives. In contrast to this paper, Ortega and Verdugo (2014) uses the cell approach of Borjas (2003) that exploits variation in immigration across cells of education and experience instead of local labor markets. Dealing with the endogeneity of immigration is difficult in the cell approach while using local labor markets provide us with a credible instrument to deal with the endogeneity of immigration. Differences in the treatment of the endogeneity of immigration might explain the stark differences in the results of these papers.

developed into an econometric model in section II. After explaining in section III how this model is applied to the data, sections IV and V characterize the observed reallocation patterns of natives and the impact of immigration on wages and days worked, respectively. Finally, section VI checks the robustness of the results, and section VII concludes.

I) Conceptual Framework

To set the stage for the empirical analysis, we describe a simple extension of a Roy model à la Gibbons *et al*. (2005) that we use to analyze the patterns of sorting in response to immigration as in De la Roca (2017). The economy is composed of different local labor markets ("locations" hereafter for brevity). The production function of location *l* in period *t* can be written as $Y_{lt} = A_{lt} L_{lt}^{1-\sigma}$, where Y_{lt} is output, L_{lt} is the total quantity of labor in the location, A_{lt} is total labor productivity, and $0 < \sigma < 1$.[7] As in Combes, Duranton, and Gobillon (2008), workers (denoted by *i*) are perfect substitutes but heterogeneous in the number of efficiency units of labor e_{ilt} they supply. We abstract from labor supply decisions at the intensive margin and assume that each worker provides one unit of labor. As a result, the aggregate amount of labor in location *l* is given by $L_{lt} = \sum_{i \in J_l} e_{ilt}$ where J_l is the set of workers in location *l*.

Local labor markets differ in their returns to unobserved characteristics. We assume that the efficiency labor units of a type- *i* worker (e_{ilt}) in location *l* can be decomposed as $\log e_{ilt} = \eta_l \alpha_i$, where the term η_l captures location-specific returns to unobserved worker characteristics α_i. For simplicity, a higher index *l* is assigned to a location with higher returns to unobserved ability in that location, i.e., $\eta_l > \eta_{l-1}$ for all *l*.[8] With competitive labor markets,

[7] With constant returns to scale, immigration has no effects on wages once the capital stock has adjusted (Borjas 2014). Here, capital is omitted, which amounts to assuming it does not immediately adjust to immigrant inflows. Whereas the relatively long intercensal period implies that the estimated effects will be partly driven by the adjustment of capital, this issue is likely to be somewhat milder for France, as censuses take place every 7 to 9 years, instead of every 10 years as in the U.S.

[8] Our model imposes a ranking of locations and ignores the potential complementarity/substitutability among groups of workers with different skills which is a key ingredient of the canonical model (Dustmann, Schönberg, et Stuhler 2016).

the log wage w_{ilt} of worker *i* in location *l* in period *t* is given by the log marginal product of labor:

$$w_{ilt} = B_{lt} - \sigma \log L_{lt} + \eta_l \alpha_i, \tag{1}$$

where $B_{lt} = \log\left((1-\sigma)A_{lt}P_{lt}\right)$ and P_{lt} is the price of the good produced in location *l*.

Assuming no mobility costs, workers choose the location offering the highest wage given their skills. The equilibrium is thus characterized by a set of ability thresholds denoted v_l and an allocation such that no worker gains by moving to another location. Thus, the unobserved ability of individuals choosing to work in location *l* satisfies $v_{l-1} < \alpha_i < v_l$ where:

$$v_{l-1} = \frac{B_{l-1,t} - B_{l,t} - \sigma\left(\log L_{l-1,t} - \log L_{l,t}\right)}{\eta_l - \eta_{l-1}}. \tag{2}$$

Firms can employ natives N_{lt} or immigrants I_{lt}, i.e., $L_{lt} = N_{lt} + I_{lt}$. Consider now an exogenous inflow of immigrants $\Delta I_{l,t}$ into location *l* and assume, as in Borjas (2006), that immigrants are not mobile across locations. Before any reallocation of natives across locations has taken place, we can see from (2) that the immigration inflow raises the threshold by $\Delta v_{l-1} \simeq \frac{\sigma}{\eta_l - \eta_{l-1}} \frac{\Delta I_{l,t}}{L_{l,t}}$ and the natives with the lowest unobserved productivity in location *l* move to location *l-1*. Similarly, $\Delta v_l \simeq \frac{-\sigma}{\eta_{l+1} - \eta_l} \frac{\Delta I_{l,t}}{L_{l,t}}$, and the most productive natives in location *l* move to location *l+1*.

To illustrate these movements, Figure 1 depicts a three-location economy where an exogenous immigration inflow into location 2 results in a fall in wages from $w_{i2t}(\alpha_i)$ to $w'_{i2t}(\alpha_i)$ that pushes workers with unobserved ability $v_1 < \alpha_i < v'_1$ away from location 2 and into location 1 and workers with unobserved ability $v'_2 < \alpha_i < v_2$ into location 3. Although these reallocations attenuate the initial effect of immigration in location 2, they also drive down wages in other locations and raise (lower) the average ability in location 1 (location 3) until a new equilibrium is reached.

An important implication of the model is that the wage loss of a native worker following immigration depends on whether he or she changes location and, for a mover, on his or her ability. Specifically, Appendix A1 shows that wage losses among location-2 stayers are homogenous and always larger than the wage losses of movers to both locations 1 and 3.[9]

Another important implication is that mobility in response to immigration affects local wages through two distinct channels: first, by lowering the initial impact of immigration on the local labor supply, as previously highlighted by Borjas, Freeman, and Katz (1997); second, by changing the distribution of the unobserved ability of natives in the location. To see this, let λ_{lt} be the parameter that characterizes how native employment in the location adjusts after the immigration inflow, i.e., $N_{l,t} = N_{l,t-1} - \lambda_{lt}\Delta I_{l,t}$. Then, we obtain that

$\log\left(\frac{L_{l,t}}{L_{l,t-1}}\right) = \log\left(1+\frac{(1-\lambda_{lt})\Delta I_{l,t}}{L_{l,t-1}}\right) \simeq \frac{(1-\lambda_{lt})\Delta I_{l,t}}{L_{l,t-1}}$. Combining (1) with this last expression, the change in the average log wages (Δw_{lt}) in location l can be approximated by:

$$\Delta w_{lt} \equiv w_{l,t} - w_{l,t-1} \simeq \Delta B_{lt} - \sigma(1-\lambda_{lt})\frac{\Delta I_{l,t}}{L_{l,t-1}} + \eta_l\left(\alpha_{l,t} - \alpha_{l,t-1}\right) \qquad (3)$$

where $\alpha_{l,t}$ denotes the average unobservable ability in the location. Eq. (3) makes it clear that, as noted by Borjas (2006), outflows of natives captured by the parameter λ_{lt} reduce the local effect of immigration on labor supply.

A second issue neglected in the literature so far is that, if movers are selected, changes in wages also reflect changes in average ability in the location captured by $\eta_l(\alpha_{l,t} - \alpha_{l,t-1})$. As

[9] The wage losses of downward movers are *increasing* in their ability because the opportunity cost of giving up location 2 is larger for those workers with higher returns to ability. Among upward movers, the losses are *decreasing* in the workers' ability, because the returns from moving to location 3 are larger for those natives with a higher ability.

discussed below, when these compositional changes are not accounted for empirically, their presence might bias naïve estimates of the impact of immigration on wages. As these compositional changes reflect a causal effect of immigration on the local labor market, they can bias the estimates, even when immigrant inflows $\Delta I_{l,t}$ are uncorrelated with local labor demand shocks $\Delta B_{l,t}$, such as when a natural experiment or an instrumental variable is used to estimate the model. As we discuss below, a straightforward solution to deal with changes in composition is to use panel data and focus on a balanced sample of workers. As workers are similar across periods, we have $\alpha_{l,t} = \alpha_{l,t-1}$ and the third term in Eq. (3) disappears.

The previous model has several limitations. The first concern is that the absence of idiosyncratic preferences for locations (counterfactually) implies that only the marginal workers at the top or at the bottom of the wage distribution move across locations. Such assumptions can be relaxed without changing the conclusions as we show in Appendix A2.

A second limitation is that immigration might influence not only wages but also labor supply and the risk of unemployment. The effects on unemployment are particularly important to address for France, as unemployment levels were high over the study period.

A third strong assumption is that all moves are explained by differences in wages, while local amenities have also been shown to respond to immigration (Saiz 2003; 2007). In a more general model, lower housing costs and other differences in local amenities also affect the utility of movers (Rosen 1979; Roback 1982; Moretti 2011).

II) Econometric model

Eq. (3) is applied to the data by using variation in the share of immigrant employees across commuting zones *l* and census years *t* to identify the model. In addition to estimating the model using all prime-aged males employed in the commuting zone, we allow the effect of immigration to vary across workers in different occupation groups *k*. We describe in detail the data we use in the next section.

As wages vary with age and immigrants might move to locations where, as a result of higher labor demand, workers are younger (Autor et Dorn 2009), we residualize wages with a regression of log wages on age dummies estimated separately for each occupation group and census year.[10] We also assume that the location-specific term B_{lt} in (3) can be decomposed into a time and a commuting zone fixed effect plus an orthogonal error term potentially correlated with local immigrant inflows and use average outcomes at the commuting zone level to facilitate inference (Donald et Lang 2007).[11] Taking first differences to eliminate time-invariant commuting zone-level wage differences, our baseline regression model is given by:

$$\Delta w_{lt}^{k} = \tilde{\gamma}_{t}^{k} + \beta^{k} \Delta p_{lt} + \mathbf{Z}_{l,t-1}^{'} \varphi_{t}^{k} + \nu_{lt}^{k} \qquad (4)$$

where Δw_{lt}^{k} is the average change in log residual wages for workers in commuting zone l and occupational group k and $\Delta p_{lt} = \frac{\Delta I_{l,t}}{L_{l,t-1}}$ measures the increase in the labor supply due to immigration defined as the ratio between the change in immigrant employees $\Delta I_{l,t}$ over the initial number of employees in the commuting zone $L_{l,t-1}$.[12] As log wages are used as the

[10] This amounts to subtracting from the initial wage the average wage of the corresponding age group in the relevant year. As the sample starts in 1976, we do not observe full labor market experience for the earliest cohort of workers, and so we use age as a proxy for labor market experience. Using observed experienced when available, or, more generally, unresidualized wages, does not change the results.

[11] From Eq. (3), the average residual wages of workers in occupation k and commuting zone l can be approximated by $w_{lt}^{k} = \gamma_{t}^{k} + \gamma_{l}^{k} - \sigma \log L_{l,t}^{k} + \eta_{l}^{k} \alpha_{lt}^{k} + u_{lt}^{k}$ where α_{lt}^{k} denotes the average worker's unobserved ability in the cell and η_{l}^{k} his or her cell-specific return. We assume that following an immigration shock in location l, a share θ^{k} of immigrants ends up in occupation k, and as previously, the adjustment in the number of natives in the occupation/commuting zone is governed by λ_{klt}. Taking first-differences (which eliminates commuting zone fixed effects γ_{l}^{k}), denoting $\tilde{\gamma}_{t}^{k} = \gamma_{t}^{k} - \gamma_{t-1}^{k}$, and assuming that $\Delta u_{lt}^{k} = \mathbf{Z}_{l,t-1}^{'} \varphi_{t}^{k} + \varepsilon_{lt}^{k}$ where ε_{lt}^{k} is an orthogonal error term, we get (4) $\Delta w_{lt}^{k} = \tilde{\gamma}_{t}^{k} - \sigma(1-\lambda_{klt})\theta^{k} \left(\Delta I_{l,t} / L_{l,t-1}\right) + \eta_{l}^{k} \left(\alpha_{lt}^{k} - \alpha_{l,t-1}^{k}\right) + \mathbf{Z}_{l,t-1}^{'} \varphi_{t}^{k} + \varepsilon_{lt}^{k}$ where the coefficient β^{k} captures the average of $-\sigma(1-\lambda_{klt})\theta^{k}$ across commuting zones.

[12] The immigration shock is divided by the initial number of employees as suggested by Card and Peri (2016), which avoids a mechanical relationship with the dependent variable when we analyze the outflow response of natives.

dependent variable, our parameter of interest β^k directly measures the impact on wages of a one percentage point immigration-induced increase in the total number of workers.[13]

The vector $\mathbf{Z}_{lt-1}^{'}$ is a set of commuting zone-specific controls, the effects of which are allowed to vary flexibly across periods through φ_t^k. To account for the fact that commuting zones of different sizes or specializations might experience different wage trends, this vector includes the log of the initial number of employees and the initial share of employment in the tradable, non-tradable and construction sectors.[14] The first-differenced time dummies $\tilde{\gamma}_t^k$ account for common wage growth between two census years.

Notice that following recent work by Dustmann *et al*. (2013), among others, we use the commuting zone-wide immigration ratio Δp_{lt}, and we do not assign immigrant workers into specific occupation groups *k*.[15] How much immigrants compete with natives in a group is captured in the estimates of the parameter.

Estimation method

According to Eq. (3) of the theoretical model, if there is selective reallocation in response to immigration, the error term can be decomposed as $\nu_{lt}^k = \eta_l^k \left(\alpha_{lt}^k - \alpha_{l,t-1}^k \right) + \varepsilon_{lt}^k$, where $\eta_l^k \left(\alpha_{lt}^k - \alpha_{l,t-1}^k \right)$ captures changes in the average unobserved characteristics of workers in the cell and ε_{lt}^k is an error term. An unbiased estimate of β^k will thus be obtained if, conditional on other variables, immigrant inflows are orthogonal to each part of this error term.

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[13] More formally, this parameter captures the semi-elasticity of wages to the share of immigrant employees in the commuting zone.

[14] Industry composition is potentially endogenous but in practice, including these variables has little effect on our estimates.

[15] We proceed in this way for the same three reasons detailed in Dustmann *et al.* (2016). First, such a procedure is immune to any misclassification of immigrants that could arise because of, among other reasons, the "downgrading" phenomenon. Second, it would be very difficult to find a convincing instrument for changes in the number of immigrants in a specific occupation. Third, this makes the estimated parameters easily interpretable and of direct policy relevance as they identify the *total* effect of immigration on a group of natives, instead of the effect of a specific group of migrants. One limitation of such approach is that it does not account for differences in the composition of immigration across commuting zones which might be important.

First, a standard issue is that immigrant inflows might be correlated with the second part of the error term, ε_{lt}^{k}, if immigrants are located in commuting zones with higher labor demand. To address the endogeneity of immigrant inflows, we adopt a shift-share instrumental variable approach following Card (2001) and Cortes (2008). We describe the construction of this instrument below.

Second, to eliminate $\eta_{l}^{k}\left(\alpha_{lt}^{k}-\alpha_{l,t-1}^{k}\right)$, we use panel data to estimate Δw_{lt}^{k} using a balanced panel of native workers observed before and after the immigrant inflow for each first difference. Instead of using the current location of workers as in the literature that relies on cross-sectional data, our approach is to use changes in the wages of workers that worked in the baseline commuting zone *l* in *t-1*. As we use the baseline and not the current commuting zone to estimate changes in wages, the sample considers within a given location workers who remained in *l* and workers who moved to work in another commuting zone between the two periods. As commuting zones might differ in their local amenities and housing markets, we also document how the characteristics of commuting zones change for movers, which is important for interpreting the result and assessing how mobility affects the utility of movers.

We also assess whether the local impact of immigration depends on natives' baseline occupation *k* using the French one-digit level classification. We consider separately (i) managers, (ii) office clerks, commercial employees and technicians, (iii) skilled blue-collar workers and (iv) unskilled blue-collar workers.[16] For locations, if we are focusing on a specific occupation *k*, we follow workers in that occupation into the second period *t* independently of whether they remained in the same occupation.

One limitation of using first differences is that only workers with observed wages in both years *t* and *t-1* are included in the sample. This restriction requires that they have worked

[16] The group of blue-collar workers is particularly large in the French classification system as it includes drivers and agricultural workers in the skilled and unskilled groups, respectively. The data appendix details the occupations included in these groups.

a least one day during both years of the first difference. To moderate the eventual biases produced by these restrictions, we focus on prime-aged male workers who are strongly attached to the labor market. We show in online appendix A1 that immigration does not affect the probability of reporting a positive number of days worked in the second period for this group of workers.

Mobility and Selection

We also directly investigate whether immigration influences the probability of a worker changing commuting zones. In contrast with the previous literature, we allow the effect of immigration on mobility to vary *within* groups in order to identify the existence of selective reallocations as predicted by the theoretical model. We consider the following linear probability model:

$$Move_{ilt}^{k} = \gamma_{r}^{k} + \beta_{k}\Delta p_{lt} + \Gamma_{1k}\tilde{w}_{il,t-1}^{k} + \Gamma_{2k}(\tilde{w}_{il,t-1}^{k} \times \Delta p_{lt}) + \mathbf{Z}_{lt}^{'}\varphi_{kt} + \varepsilon_{ilt}^{k} \tag{5}$$

where $Move_{ilt}^{k}$ is individual *i* residual probability of working in a different commuting zone from commuting zone *l* in period *t,* γ_{r}^{k} is a regional fixed effect, $\tilde{w}_{il,t-1}^{k}$ is the individual's percentile-rank in the initial residual wage distribution in the *(l,k)* cell, and the vector of commuting zone controls $\mathbf{Z}_{lt-1}^{'}$ is defined as previously.[17] In this model, Γ_{2k} captures differences in the probability of moving and is allowed to vary within groups.[18] For wages, our dependent variable is a residual probability, obtained by regressing the raw mobility probability on age dummies separately for each occupation group and census year.

Unlike wages that are estimated in first differences, time-invariant commuting zone-level factors that influence the probability of moving are not eliminated. To address this issue,

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[17] We use the initial rank in the *residual* instead of the *observed* distribution to avoid differences in rank explained only by age differences. However, using instead the rank in the observed distribution does not change the results.

[18] Our theoretical model predicts the potential simultaneous presence of positive selection (for upward movers) and negative selection (for downward movers). Whereas this might justify a nonlinear specification of the percentile rank in the model, we find empirically that a linear term captures differences in selection patterns rather well and is simpler to interpret.

we include 12 regional fixed effects γ_r^k that account for permanent differences in mobility rates across regions. The estimation of this model relies on 2SLS, and both Δp_{lt} and $\left(\tilde{w}_{il,t-1}^k \times \Delta p_{lt}\right)$ are treated as endogenous.[19]

Choice of weights in the regressions

In the absence of reweighting, the mobility regressions of Eq. (5), which are estimated at the individual level due to the presence of an interaction term, assign a weight to commuting zones proportional to their number of observations. On the other hand, the wage regressions of Eq. (4) exploit commuting zone averages and thus give the same weight to each commuting zone. To make estimates from both models comparable, we weight the mobility regressions of Eq. (5) with the inverse of the number of observations per commuting zone, thus giving a similar weight to each commuting zone. Our approach of giving the same weight to each commuting zone also allows us to compare the estimates across occupational groups, as the weights do not vary with their distribution across commuting zones.[20]

III) Empirical Implementation

Data Sources

Our primary data source is the matched employer-employee administrative panel DADS (*Déclaration Annuelle de Données Sociales*) collected by the French National Institute for Statistics (INSEE).[21] The DADS panel is available annually from 1976 to 2007, except for 1981, 1983 and 1990, when the data were not collected. The sample includes individuals born in even-numbered years in October, which amounts to approximately 4% of employees.[22] For each job spell, the panel reports earnings, the number of days worked and the location of the

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[19] Instead of using a linear probability model, we also estimated Eq. (5) using a latent variable approach with the Newey (1987) control function estimator. The estimated marginal effects at the sample mean were very similar to the 2SLS estimates reported below but the estimates were also more imprecise. These results are available upon request.

[20] Using weights proportional to the sample size in the commuting zone would change the importance of each commuting zone when the distribution of groups varies across commuting zones, as it does for blue-collar workers and managers, for example.

[21] This dataset is based on compulsory fiscal declarations by all employers for each worker and is considered very reliable, as misreporting is punishable with fines.

[22] 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 (Aeberhardt, Givord, et Marbot 2016). As the number of hours is very noisy, we have chosen not to use it.

job at the municipality level. The data also report the residency of the worker at the more aggregated department (*département*) level.[23]

As the DADS panel does not indicate the nationality of the workers but only whether they are foreign born or not, we define native workers in this sample as those born in France.[24] As the data come from annual employers' declarations, the self-employed and individuals who are not employed for a full year are not covered in that year. In addition, public sector employees and civil servants were only fully covered starting at the end of the 1990s.[25]

The models are estimated by combining data on natives' wages and number of days worked from the DADS panel with the number of immigrants in each commuting zone based on the Census. The censuses took place in 1968, 1975, 1982, 1990, 1999 and 2007. We obtained access to 25% extracts of the population (20% in 1975), which diminishes sampling error and thus renders our estimates immune from attenuation biases as identified in Aydemir and Borjas (2011).[26] Unlike the DADS panel, the Census includes information on the country of origin that allows us to construct an instrumental variable for local immigrant inflows. As is conventional, an immigrant is defined as a foreign-born individual who was not French at birth.

Local labor markets are defined using the 2010 definition of commuting zones (*zones d'emploi*) designed by the French Statistical Institute, which aggregates daily commuting patterns into 286 labor market regions. Regressions are thus estimated using 286 commuting zones and changes in the immigration ratio as measured by four first-differences: 1975-82, 1982-90, 1990-99, 1999-2007.

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[23] As we exclude Corsica, our sample contains 93 departments in mainland France. Whereas the department of residency is always reported in the data, the municipality of residency of the worker is only reported after 1993.

[24] Individuals born in Algeria before its independence from France in 1962 are reported in the DADS as being born abroad independently of whether they are of European or Arab/Berber origin. For this reason, Europeans born in pre-independence Algeria are not counted as natives. From the Census, we estimate that the share of European Algerians among 18-65 years old natives is 2.2% in 1982 and 1% in 2007. More generally, the share among French-born citizens who are born abroad is small and declining over time: 4.4% and 3.2% in 1982 and 2007, respectively.

[25] See the Data Appendix for details on sample coverage. Additionally, the DADS data do not include information on education.

[26] We accessed both datasets through the French secure data access center (CASD); see https://www.casd.eu/en/

Construction of the sample

As the long-term unemployed (more than a year) are not included in our sample, we focus on prime-aged males for whom long-term unemployment is less likely to occur. We include in our sample all native males aged 25-50 in any given census year who are also observed in the following census year. As the distance between consecutive censuses varies from 7 to 9 years, the ages of workers included in the second period span from 31-56 for 1975-82 to 34-59 for 1982-90 (see Panel A of Table A3), but their age is always the same in the first period.[27]

Table A3 in the online Appendix reports the size of the different occupational subsamples across census years. As shown in Appendix Table A3, even if we are able to follow most workers over long periods of time,[28] approximately 20-25%[29] of the workers observed in a given census year are not observed in the following year and thus cannot be included in our sample. Although clearly nonnegligible,[30] most of the attrition appears to be explained by long-term individual transitions towards noncovered sectors rather than by transitions to nonemployment.[31] We also document in online Appendix A1 that attrition is not systematically correlated with immigration.

Immigration into France: Key Figures

In 2007, 5.2 million immigrants lived in France, accounting for 8.2% of the population, a smaller proportion than in the US or the UK (14.9% and 11.5% in 2005, respectively; see Dustmann, Frattini, Preston, 2013, p. 153). Table A1 in the online Appendix compares the annualized percentage share of immigrant inflows in France and the US for the period 1968-

[27] See Data appendix and Appendix Table A3 for the exact match between Census, DADS and age. As we residualize wages (and more generally all other outcomes we consider) using age dummies at each period, that procedure should absorb systematic differences in wage growth across periods related with differences in length of time between censuses. Additionally, the results are similar when defining a common age interval in the second (instead of the first) period of each first difference.

[28] Individuals are observed on average for 13.5 years in our sample and up to 25-30 years for some cohorts.

[29] Reflecting the decrease in the number of coding errors in individual identifiers, attrition rates become lower over time.

[30] At the same time, attrition rates are not higher than for other widely used panel datasets and the total number of observations in the DADS is much larger. The PSID has, for instance, an attrition rate of 50% between 1968 and 1989 (Fitzgerald, Gottschalk, et Moffitt 1998) and the BHPS has a 33.3% attrition for 1991-98 (Contoyannis, Jones, et Rice 2004).

[31] Indeed, when we allow the individuals to be observed in three- or five-year windows around census years, which should be sufficient to include most long-term unemployment spells, attrition rates decline by only approximately 4 to 6 p.p.

2010. The size of immigration inflows into France was broadly similar to the US inflows during the 1970s, less than half in the 80s and 90s, and 20% lower in the 2000s.

Importantly, and in contrast with the stable country-of-origin mix characterizing U.S. immigration since the 1980s (Jaeger, Ruist, et Stuhler 2018), the composition of immigration in France has dramatically varied across decades (Pan Ké Shon et Verdugo 2015). Specifically, Table 1 shows that this period is characterized by an important increase in immigration from sub-Saharan Africa and a fall in Asian immigration. Panel A in Table 2 shows that there are significant variations in immigrant inflows across regions and over time.[32]

The number of immigrants also varied substantially across occupations: Panel B in Table 2 shows that the share of foreign-born workers increased rapidly over the study period among managers but declined for technicians and blue-collar workers during the 1990s before increasing again in the 2000s. Panel C shows that foreign-born individuals are much more likely to work in blue-collar occupations than natives, particularly in unskilled blue-collar occupations. Table A2 in the online Appendix shows that foreign-born workers are more often at the bottom of the wage distribution within each occupational group, particularly among skilled blue-collar workers.

Accounting for Endogenous Immigrant Inflows

To account for the potential endogeneity of immigrant inflows, we construct a shift-share instrument à la Card (2001), which predicts local immigrant inflows by combining the initial proportion of co-nationals in the commuting zone in a reference period with the country-wide inflow by nationality. Specifically, for each country of origin *c*, the predicted inflows are obtained by multiplying the share of immigrants from that country $\pi_{cl,t_0} = \frac{I_{cl,t_0}}{I_{c,t_0}}$ in reference

[32] Over the study period, the location choice of immigrants does not appear to be systematically driven by the share of any particular group of industries. Verdugo (2016) finds that the local supply of public housing, the size of ethnic networks and differences in local labor demand had much more influence on the location choice of immigrants than the local industrial composition.

period t_0 in commuting zone *l* by the change ΔI_{ct} in the number of immigrants from the same country at the national level between Census *t-1* and Census *t.* Our instrument is then obtained by adding up across countries for each commuting zone and dividing by the initial population in the commuting zone, i.e.,

$$\Delta \tilde{p}_{lt}^{t_0} = \sum_c \pi_{cl,t_0} \frac{\Delta I_{ct}}{L_{lt-1}}.$$

We construct the instrument with the 54 different countries of origin consistently reported across Censuses. We construct two alternative instruments that differ with respect to the reference period of the initial settlement pattern. In our baseline specification, we set our reference period to $t_0 = 1975$, as this year provides the earliest initial settlement pattern with a sufficient number of immigrants from Asia and sub-Saharan Africa, which is needed to predict the location choices of immigrants from these countries in the 1990s and 2000s. As reported in Table 3, this instrument proves to be weak in separate estimates for recent periods, as recent inflows include nationalities that were rare in the 1970s. To address this issue, we construct an alternative instrument using a moving base period $t_0 = t - 2$.[33] While there is no definitive argument for preferring one instrument over the other, we report below that the results with both instruments are qualitatively similar.

As shown by Jaeger *et al.* (2018) for the US, using the shift-share instrument is problematic when the location choice of immigrants is stable over time.[34] Table 1 shows that this problem is likely to be milder in France, as local immigrant inflows are much less correlated than for the U.S. With the exception of the 1990s, the autocorrelation coefficients

[33] When constructing the instrument using a moving base period $t_0 = t - 2$, we had to make an exception when predicting the lagged inflows for the 1975-82 first difference with the $t - 2$ census, as no census earlier than 1968 was available. As a consequence, we use the distribution of immigrant groups across commuting zones in 1968 to predict both the 1975-82 and 1982-90 first difference, the 1975 distribution to predict the 1990-99 first difference and the 1982 distribution to predict the 1999-2007 first difference.

[34] See also Borjas (1999), Pischke and Velling (1997) and Amior (2018) for critiques of the shift-share approach.

for both the observed immigration shock, Δp_{lt}, and the shock predicted by our instrument $\Delta\tilde{p}_{lt}^{75}$, are generally between 0.4 and 0.7 depending on the decade and thus well below the 0.9 correlation reported by Jaeger *et al.* (2018 Table 3) for the U.S.

Table 3 examines how well our instrument predicts changes in the immigrant ratio. Panel A reports regressions using stacked first differences between census years. Our past settlement instrument is a strong predictor of immigrant inflows, with a first stage F-stat of 38 and 58 for the $t_0 = 1975$ and $t_0 = t - 2$ instruments, respectively.[35]

Following Jaeger *et al.* (2018), we examine how the results change when controlling for past-immigrant inflows. As both the contemporary and lagged instruments use the distribution from the same base period year, both instruments should be highly correlated if variation in the national origin of immigrants is stable over time. Reassuringly, the results in columns 3 and 6 suggest that there is sufficient variation in national inflows to separate the two shocks, as the contemporary instruments are stronger predictors of contemporary inflows than their lagged counterparts.

Finally, Panel B assesses the performance of the instruments by decades. For the instrument with base period $t_0 = 1975$, the first-stage F-stat declines in recent periods, and the model seems unable to separate the overlapping shocks in the 1980s and 1990s. In contrast, the instrument using base period *t-2* remains reasonably strong across decades.

IV) Immigrant Inflows and Natives' Mobility Patterns

In this section, we document how immigration affects the commuting zone in which natives are employed, looking separately at outflows and inflows. In the next section, this information is then exploited to shed light on why alternative estimates of the impact of immigration on wages and employment might differ.

[35] As inference is based on robust standard errors clustered at the commuting zone level, we report the Kleibergen-Paap F-stat.

Natives' outflows

First, we estimate whether immigration induces natives to move to a job in a different commuting zone. In Table 4, we report regressions where the dependent variable is the age-adjusted probability that natives work in a different commuting zone between two consecutive censuses.[36] The occupational groups correspond to the natives' baseline occupations before the immigrant inflow.

Panels A and B report OLS and 2SLS estimates of the impact of immigration on mobility that do not allow the probability to vary with the initial residual wage. When considering the entire sample, both the OLS and 2SLS estimates indicate that higher immigration into the location is associated with a substantially higher probability of natives getting a job in a different location. The coefficients of the 2SLS estimates are very similar across groups albeit they are statistically insignificant for managers and unskilled-blue collar workers. In terms of magnitudes, the 2SLS estimates for skilled blue-collar workers indicate that a 1 p.p. increase in labor supply due to immigration into the commuting zone raises the outflow rate of these workers by approximately 0.8 p.p.

In Panel C, we add an interaction term between the initial wage rank and the immigration inflow to the model to investigate whether there are important differences within occupational groups in the probability of moving. Clearly, the coefficient of the interaction term is quite large and statistically significant for blue-collar workers and for managers, thus indicating that the effects of immigration vary within these groups. To quantify the importance of selection, we compare the effect of a 1 p.p. increase in labor supply due to immigration on the mobility rates of workers initially at the top and bottom of the initial residual wage distribution (rank 1 and 0, respectively) in the bottom panel. For blue-collar workers, the estimates suggest that although immigration does not influence mobility at the

[36] The distribution of the residual wage rank varies slightly across occupation groups because of small differences in the discretization of that variable. As a result, the first-stage of the regressions reported in Table 4 might be slightly different across occupation groups.

top of the wage distribution, it does substantially raise mobility at the bottom –by 1.6 and 1 p.p. for skilled and unskilled blue-collars, respectively. This result is consistent with the evidence that immigrants are mostly located at the lower end of the blue-collar wage distribution for each group. In contrast, for managers, we find a stronger and statistically significant effect of immigration on those initially at the top relative to the bottom.

Overall, these results imply that the endogenous mobility of natives not only diminishes the local impact of immigration but also changes the composition of native workers in the commuting zone. These compositional changes potentially affect estimates of the wage impact of immigration based on average wages across commuting zones.

Differences in the origin and destination commuting zone

To understand the mobility decision and its consequences for the utility of movers, we investigate how the characteristics of origin and destination commuting zones differ for natives that move because of immigration. Using all the observed commuting zone moves, we estimate the following model with 2SLS:

$$C^k_{idt} - C^k_{iot} = \gamma^k_t + \gamma^k_{or} + \beta^k_l \, \Delta p_{ot} + \varepsilon_{it}$$

where $C^k_{idt} - C^k_{iot}$ measures how individual *i*'s destination (*d*) and origin (*o*) commuting zones (measured based on job location) differ in characteristic *C*, Δp_{ot} is the immigration shock in the origin location, γ^k_t is a time fixed-effect and γ^k_{or} is a region-of-origin fixed-effect.[37]

Estimation results are reported in Table 5, where the dependent variables in panels A and B are the difference in the share of immigrants and in the increase in that share between the origin and destination commuting zones, respectively. The results indicate substantial differences between the origin and destination commuting zones. Clearly, movers move to locations with a lower share of immigrants and where the share of immigrants among

[37] The characteristics of the origin and destination commuting zones are both evaluated in period *t* in order to capture their characteristics after the immigration shock.

employees increases less rapidly. In panel C, we instead consider differences in rents between locations as the dependent variable.[38] We find—consistent with Albert and Monras (2017) and Bilal and Rossi-Hansberg (2018)—that larger immigration inflows in the origin location are associated with outflows towards destinations with lower housing costs. Overall, these differences in the characteristics of commuting zones might have important consequences for the utility of movers.

Native Inflows

Next, we investigate whether inflows of immigrants into a commuting zone deter natives from moving into a job in those locations, as suggested by Filer (1992) and recently by Dustmann *et al.* (2017) and Monras (2018). In Table 6, we report regressions using the native inflow rate into the commuting zone and occupational group as the dependent variables.[39] In Panel A, we report OLS estimates that do not take the endogeneity of immigrant inflows into account. The results indicate that immigrant inflows are positively correlated with native inflows into the same commuting zone. When we take into account the endogeneity of immigration using our shift-share instrument, the results are dramatically different. In the 2SLS estimates reported in Panel B, we find that immigration *lowers* native inflows into the same commuting zone for blue-collar occupations. The coefficients suggest that a 1 p.p. increase in labor supply due to immigration lowers the inflow rate of natives into the same location by 0.5 p.p. (0.8 p.p.) for those natives belonging to a skilled (unskilled) blue-collar occupation. At the same time, no statistically significant effects are found for other occupational groups.

In Panel C, we report results obtained using individual level data that allow the effect of immigration on inflows to vary with the initial wage rank. For blue-collar workers, the coefficient of the interaction term suggests that an increase in labor supply due to immigration

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[38] Data on rents is only available after 1999. See the data appendix for information on the construction of this variable.

[39] The inflow rate is defined as the ratio between the numbers of newly arrived natives in Census year *t* divided by the initial number of natives in *t-1*. A newly arrived worker must have been observed in a different commuting zone in the previous period, i.e., we require him to be observed twice.

has a stronger effect on inflows from workers that were initially in the bottom of the wage distribution of their origin commuting zone. For the other groups, estimates of the coefficient associated with the interaction term are very imprecise and differences in the effects of immigration on inflows tend to be statistically insignificant.

Effects on the number of native employees

Panel D in Table 6 summarizes how the previously reported effects of immigration on inflows and outflows affect the growth of the population of native employees.[40] In the first column, where native employees are considered irrespective of their occupation, the point estimate is close to one which implies that the arrival of immigrant employees is followed by a reduction of the same number of native employees. The other columns show that most of these effects are driven by a decline in the number of native employees in blue-collar occupations and to a lower extend for technicians and clerks. In contrast, immigration has no statistically significant effect on the number of native employees that are managers.

Comparisons with other studies

Although other studies have not examined differences in responses *within* occupation groups, our estimates are quite similar to recent IV estimates reported in the European literature. Using data from 110 Italian provinces over 10 years, Mocetti and Porello (2010, Table 10, p. 436) report that, for low-educated natives, a 1 p.p. increase in labor supply due to immigration increases outflows by 0.9 p.p. and decreases inflows by 0.6 p.p. Using 11 regions in the UK, Hatton and Tani (2005, Table 7, F355) estimate a 0.3 p.p. decrease in the inflow rate as a consequence of a 1 p.p. increase in immigration.[41] These estimates are in line with the aggregate estimates reported here for skilled blue-collar workers, where a 1 p.p. increase in immigration increases outflows by 0.8 p.p. and decreases inflows by 0.5 p.p.[42]

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[40] By definition, the growth rate of the population can be decomposed as the difference between the inflow rate and the outflow rate.

[41] Such lower estimates might be explained by the fact that the other studies use more aggregated geographical zones.

[42] See Table 4, panel B, column 4 and Table 6, panel B, column 4, respectively. These estimates are lower than those reported by Borjas (2006) for the US, who finds a 2.3% decline in the population in response to a 1 p.p. increase in the immigrant share at the census division level. These results contrast with Peri and Sparber (2011, Table 6), which reports a positive correlation between inflows of natives and

V) Adjustments through Wages and Days Worked

We now investigate how native mobility following immigration affects local estimates of the impact of immigration on natives' wages and annual number of days worked.

Effects on Daily Wages

To capture the effect of immigration on the price of labor, we start with specifications using the residual log daily wages, simply computed by dividing annual earnings by annual days worked. We first report estimates in Panels A and B in Table 7 using changes in wages using the *current* location of the job in each census year, as in a standard cross-sectional study.[43] When we use the current location, the composition of the sample across commuting zones changes between periods through potentially selective inflows and outflows of natives from the location. Both OLS and 2SLS specifications using the current location of workers indicate that average wages are positively (although not always significantly) correlated with the increase in labor supply due to immigration in the commuting zone. Taken at face value, such results are inconsistent with the hypothesis that immigration decreases wages.

In Panel C and D, we instead consider estimates where the composition of the sample does not change within each first difference as natives are allocated to their *baseline* commuting zone and to the occupation group in which they were observed during the first period of each first difference. As discussed earlier, workers that left the commuting zone or occupation group are also included in the second period.

The results reveal stark differences relative to estimates using the current location. Once changes in the composition of the native workforce are accounted for, the coefficients become negative and statistically significant for all groups except for managers. The 2SLS estimates indicate that a 1 p.p. increase in labor supply due to immigration into a commuting zone lowers

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immigrants in the US. However, neither Borjas (2006) nor Peri and Sparber (2011) used an instrument for local immigrant supply shocks, which complicates the comparisons.

[43] To facilitate comparisons, we match the age range of the sample using the current location with the sample using the baseline location. However, the composition of the sample changes between the two periods through inflows and outflows of natives from the location.

wages by approximately 0.24% for all employees. For blue-collar workers, we find that a 1 p.p. increase in labor supply due to immigration decreases wages by 0.33% and 1% for respectively the skilled and the unskilled within this group. [44]

Overall, these large differences between estimates using the baseline and the current location suggest that estimates using the current location are upwardly biased and that local compositional changes can explain the positive coefficients obtained when using the current location.[45] Interestingly, the magnitude of the estimates using the baseline-location is in line with the recent studies of Bratsberg (2012) and Dustman *et al*. (2017) that also use panel data to adjust for compositional changes in the native population.[46]

Effects on Days Worked per Worker

Next, we examine how immigration affects the employment of natives in Table 8. As we do not observe unemployment directly in the data, we use the annual number of days worked per worker as a dependent variable. While unemployment periods decrease the annual number of days worked for a worker, they cannot be distinguished in the data from periods of non-participation. However, as we focus on prime age-male workers, periods of non-participation should be relatively rare.

As in the previous analyses, we start in Panels A and B with estimates using the current location of the worker, which does not fix the composition of the sample. The estimates using the current location suggest a small and imprecise negative effect on the number of days worked. For the estimates using the baseline location reported in Panel C and D, the coefficients

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[44] We also estimated regressions weighting each observation by the square root of the sample size in the commuting zone. Using these weights should improve the precision of the estimates if the variance of the error term depends on the number of observations by commuting zones (Solon, Haider, et Wooldridge 2015). Although the coefficients remain negative, the point estimates were lower and more imprecise, which suggests a larger group component in the variance of the error term (Dickens 1990).

[45] We also estimated regressions where the immigration shock was computed relative to the number of natives in period t instead of period t-1, following Friedberg (2001), Borjas and Monras (2017) or Edo (2020). The results were virtually identical and are available under request.

[46] Using differences in the share of immigrants across occupations in the construction sector and controlling for individual fixed effects in the empirical specifications, Bratsberg (2012, Table 1, 13) reports declines in log wages between -0.5 and -0.7 as a result of a 1 p.p. increase in immigration in a specific occupation. Using an exogenous increase in the number of foreign workers commuting from the Czech border in Germany, Dustman *et al*. (2017, Table 4, 462) report that a 1 p.p. increase in immigration decreases the wages of unskilled workers by 0.2% and by 0.1% for skilled workers.

are smaller and statistically insignificant for all groups except managers. For managers, on the other hand, the coefficient is negative, economically large and statistically significant, thus suggesting that workers in this group adjust to immigration through a decrease in numbers of days worked.

Effects on Annual Wages

In Table 9, we report regression results obtained using the annual wage as the dependent variable. For most groups except managers, the coefficients are similar to those observed in regressions using the daily wage, but the estimates are more imprecise and not statistically significant. For managers, the coefficient in this specification is negative, consistent with the earlier evidence that immigration has a negative effect on the number of days worked on these workers.

Differences in adjustment between stayers and movers

In specifications using the baseline location, the estimated impact of immigration captures its impact on both stayers and movers. To understand the consequences of the mobility decision, we investigate whether there are differences in the adjustment of wages and annual employment between the two groups. We consider the following model:

$$\Delta y_{ilt}^{k} = \gamma_{kt} + \beta_{1k}\Delta p_{lt} + \beta_{2k}(lshift_i \times \Delta p_{lt}) + \beta_{3k} lshift_i + \varepsilon_{ilt}^{k}$$

where Δy_{lt}^{k} measures either the change in the residual log daily wage or log annual number of days worked for individual *i* initially observed in commuting zone *l* during census *t-1,* and $lshift_i$ is a dummy variable equal to one when the individual is working in a different commuting zone in census *t*. In this model, the coefficient β_{2k} captures differences in the adjustment of wages or the annual numbers of days worked to immigration for location-movers. We estimate the model with 2SLS using the interactions between $lshift_i$ and $\Delta\tilde{p}_{lt}^{75}$ as additional instruments, treating $(lshift_i \times \Delta p_{lt})$ as endogenous.

The estimation results reported in Table 10 suggest that the adjustment of wages and employment to immigration differs in a meaningful way between stayers and movers. For daily wages, the interaction terms are negative across all groups, which suggests that movers experience a larger decline in their daily wages, in particular among unskilled blue-collar movers for whom the negative effect of immigration on wages is twice as large as for stayers. In contrast, Panel B indicates that while immigration decreases the number of days worked by stayers, it is associated with a relative *increase* in annual days worked by movers. This implies that although mobility is associated with relatively lower daily wages for blue-collar movers, the fact that they tend to work more days might compensate for their wage losses. Consistent with this hypothesis, estimates in Panel C show that the interaction between mobility and immigration has no statistically significant negative effects on annual wages.

Taking differences in housing costs into account

As discussed earlier, differences in wages across commuting zones might not be the only factor influencing mobility decisions. In particular, the fact that location movers tend to move to work in commuting zones with cheaper housing might attenuate the consequence of their larger wage losses. To account for differences in housing costs, we follow Moretti (2013) and adjust wages by constructing local price indexes, taking into account differences in housing costs. We use alternatively 20% and 30% income expenditure share for housing, consistent with data on households with below-median incomes in France (Accardo et Bugeja 2009, 41).[47]

Regression results using housing price-adjusted daily wages are reported in Table 11 for skilled and unskilled blue-collar workers. In this table, we only use the 1999-2007 first difference, as these are the only two census years with data on local rents available at the

[47] Because we do not have data on other local prices, we do not take into account differences in the price of non-housing goods and services across locations. How much this may affect our measures of local prices is uncertain, as prices tend to be higher in large cities where a large share of immigrants live. On the other hand, Handbury and Weinstein (2015) report that prices might indeed be lower in large cities once differences in the quality of goods are taken into account, whereas Cortes (2008) finds that low-skilled immigration lowers the price of services.

commuting zone level. Although the first-stage F-stat is low which implies that these estimates must be interpreted with caution, the results are consistent with the hypothesis that cheaper housing in destination commuting zones compensates to some extent for the higher wage losses of location movers relative to stayers. Compared with the benchmark specifications in columns 1 and 4, the sign of the interaction term between immigration and mobility is reversed when wages are adjusted to account for housing costs. This suggests that differences in housing costs might be important to consider when assessing how mobility changes the utility of movers.

However, an important issue is that lower housing costs might be correlated with other differences in local amenities across commuting zones that might also affect the utility of movers. In addition, we do not observe actual changes in residency in residency in the data but only change in the location of the job. As we discuss below, some short-distance job mobility patterns might be associated with changes in commuting patterns and not change in residency that makes differences in housing costs between commuting zones irrelevant.

Additional evidence on labor market adjustments

Several additional results are reported in the online Appendix. Using long-differences regressions, we report in online Appendix A2 that immigration shocks are not persistent after 15 to 17 years. In online Appendix A3, we document that occupations are crucial to identify workers most affected by immigration, as immigrant inflows have no statistically significant effect on average wages when groups of workers are defined using quartiles of the initial wage distribution instead of occupations.

In online Appendix A4, we show that the effects of immigration on the wages of blue-collar workers appear larger in the tradable industries than in the non-tradable industries, consistent with Dustmann and Glitz (2015). In online Appendix A5, we show that the effects of immigration appear lower for workers more than 35 years of age than for those who are younger, the estimates are imprecise. In online Appendix A6, we provide results from models estimated at a more aggregated geographical level, using the location of the job across 93 departments instead of 286 commuting zones. The results are qualitatively similar but tend to be attenuated and more imprecise.

Finally, in online Appendix A7, we examine how much our results reflect changes in the residency of the worker relative to changes in commuting patterns across commuting zones. While we do not observe the commuting zone of residency, we have information on the department of residency that allows us to identify workers who both move to work in another commuting zone and change their residency to another of the 93 French departments. The results indicate that between a third and a half of the effect of immigration on job mobility is also associated with residential mobility across departments. We also find that the additional negative effects of immigration on the daily wages of movers are driven by workers who also change their department of residency.

VI) Robustness

Dealing with attrition

As explained in Section III, each first difference in our sample using the baseline location includes only prime-aged males observed twice in consecutive census years. Such requirements imply the workers have not transitioned into long-term unemployment of more than one year for the entire second year. The impact of immigration will be underestimated if some attrition reflects long-term unemployment caused by immigration.

We report alternative specifications that attempt to take into account the consequences of attrition in Table 12. We start by measuring the relevant outcome variable in a 3-year window around the Census year by computing the log of the average of that variable in that window and imputing a zero value when no observation is available. In this specification, inclusion in the sample requires only one day of work in a three-year period around both census years, which lowers the attrition rate by approximately 5 p.p. (see Table A3 in online

Appendix). With this strategy, the estimated coefficients reported in Panel A of Table 12 are very similar to those of the benchmark specification.

An alternative approach is to assume that all workers missing in the second period have below-median wages, to impute a log daily wage of zero for them in the second period, and then to use the median change in the log daily wage as the dependent variable instead of the change in the average.[48] In this case, we expect the corresponding estimates, presented in Panel C, to provide a lower bound, as all attrition is attributed to long-term nonemployment. In Panel D, following the same method, we provide "upper bound" estimates by replacing any missing annual wages in the Census year with the last observed earnings. Overall, the results from the analyses with imputed wages are quite similar to the estimates using medians but no imputations, reported for reference in Panel B. These results are consistent with the evidence in online Appendix A1 showing that attrition is not correlated with immigrant inflows.[49]

Identification

Next, we report additional estimates designed to assess the robustness of our results in Table 12. To save space, we focus on skilled blue-collar workers, as this is the largest occupational group for which a strong effect of immigration on most outcomes has been identified. We start in Column 2 using the more recent settlement pattern base period *t-2* to construct the instrument. If the estimates change significantly when more recent settlement patterns are used, this might raise concerns about their exogeneity. Reassuringly, the estimates are very similar to the benchmark results in Column 1.[50]

Another concern with the shift-share instrument is that any serial correlation in both wages and immigration at the regional level would thus invalidate the exclusion restriction

[48] See Olivetti and Petrongolo (2008) or Walker (2013) for papers examining the robustness of estimation results to attrition in this way.

[49] As the estimates of the impact of immigration on mobility might also be affected by attrition, Table A7 in the online appendix presents similar robustness checks for both mobility variables. Specifically, we assume first that all individuals not observed in the second period are movers, and then instead assume they are all stayers. The results are similar to those from using wages.

[50] We also estimated models pooling only the two most recent periods (1990-99 and 1999-2007). As the distance between the estimation period and the baseline year 1975 used to construct the instrument is increased, this reduces concerns that our estimates are driven by a correlation between the initial settlement patterns and location-level trends in the labor market. The results are remarkably robust for most outcomes.

imposed by the IV strategy. To investigate whether serial correlation is an important concern, Column 3 includes the lagged immigrant inflow as an additional (endogenous) regressor.[51] The estimates are also very similar to the benchmark, with coefficients on the lagged immigrant inflows that tend to be small and statistically insignificant.

Column 4 then tests the robustness of the results to the inclusion of 286 commuting zone fixed effects to account for constant trends at this geographical level. Although more imprecise, the estimates are similar to the benchmark in most cases. However, the coefficient for wages becomes statistically insignificant in such a demanding specification.

At the bottom of both tables, we report Arellano and Bond (1991) tests for first- and second-order correlation of the residuals. For wages, there is clear evidence of negative first-order serial correlation in the baseline specification, as should be expected given the first-differencing in the model. On the other hand, we cannot reject the absence of second-order correlation in most specifications.[52]

Further robustness checks

We report separate estimates by decades in online Appendix A8. The estimates are more imprecise, but they are consistent with the pooled estimates except for the 1990-1982 first differences. Online Appendix A9 reports estimates for wages residualized both with age dummies and with year-by-industry fixed effects to account for potential industry-specific trends in the evolution of wages at the national level. Alternatively, we also report specifications including a Bartik instrument as an additional control variable for local labor demand shocks as in Jaeger *et al*. (2018). Overall, the results are quite similar, although wage estimates are more imprecise when wages are residualized to account for industry trends.

[51] Following Jaeger *et al*. (2018), we use the contemporary and lagged shift-share as instruments in this specification.

[52] In contrast, for changes in location, we find significant first- and second-order autocorrelation. However, the results are very similar in specifications with commuting zone fixed effects or including controls for baseline mobility rates (see Table A8 in the online Appendix) except for the unskilled blue-collar workers, for which no significant effect of immigration is found in the latter case. The residuals of specifications with commuting zone fixed-effects are negatively serially correlated as should be expected in a fixed effect model (Wooldridge 2001, 270).

VII) Discussion

In this paper, we have revisited the labor market impact of immigration on natives using panel data, focusing on workers defined by their baseline location to address changes in the composition of the population of workers across local labor markets. We find that immigrant inflows are associated with native outflows from the location, but the probability of changing location varies between and within occupation groups. As a result, it is crucial to account for changes in the composition of the native workforce when estimating the wage effect of immigration using local labor markets.

There are, however, limitations to our analysis. A first limitation relates to the use of a spatial correlation approach. Consistent with evidence from other studies (Borjas 2014), the estimated effects are not entirely robust to specification changes. In particular, the magnitude of the effect depends upon the geographic definition used to estimate the model, as the results obtained using departments instead of commuting zones tend to be lower. Additionally, the internal reallocation of natives reported in the paper is consistent with the hypothesis that the effect of immigration spreads throughout the national economy.

A second limitation is that to minimize the risks of biased by long-term unemployment or participation, we have focused on prime-aged males. According to Smith (2012), low-skill immigration might disproportionately affect younger workers who were not included in our analysis. An evaluation of the impact of immigration on the labor market trajectories of young workers would be of substantial interest for future work.

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Appendices

A1. Theoretical Appendix: Gains and losses of stayers and movers

Consider the three locations economy described in the text where initially immigration raises labor supply only in location 2. From (1), the wage w_{ilt} of an individual i in location *l* and period *t* can be decomposed as

$$w_{ilt} = w_{lt} + \eta_l \alpha_i \tag{A1}$$

where $w_{lt} = B_{lt} - \sigma \log L_{lt}$ is the equilibrium wage per efficiency unit in location *l* and $\eta_l \alpha_i$ is the number of efficiency units supplied by the individual in that location. After an immigration shock in location 2, each individual re-optimizes its location choice to minimize the associated wage loss. Omitting the time subscript for brevity, we denote by (L_1^*, L_2^*, L_3^*) the new equilibrium allocation of labor and by w_l^* the wages per efficiency unit in these locations. For those individuals choosing to stay in location 2, the change in the wage is given by:

$$\Delta w_{i2}^{stay} = w_{i2}^* - w_{i2} = -\sigma(\Delta \log L_l)$$

where $\Delta \log L_l = \log L_l^* - \log L_l$ i.e. the effect of immigration is confined to the change in the wage per efficiency unit in the location and does not depend on α_i. The wage change for a 'downward' mover from location 2 to location 1 is given by:

$$\Delta w_i^{down} = w_{1i}^* - w_{2i} = \tilde{w}_1^* - \tilde{w}_2 + (\eta_1 - \eta_2)\alpha_i \tag{A2}$$

i.e. the wage change comes both from the change in the wage per efficiency unit $\tilde{w}_1^* - \tilde{w}_2$ across locations and the change in the number of efficiency units rewarded in location 1 compared to location 2 (the remaining terms in (A2)). From (A2), it is easy to see that as $\eta_1 < \eta_2$ the loss to a downward mover is increasing in α_i.

Let individual i_1 be a downward mover and individual i_0 be a stayer. The difference between the loss of i_1 and that of i_0 is given by $(w^*_{i_1,1} - w_{i_1,2}) - (w^*_{i_0,2} - w_{i_0,2})$. Using (A1), we have that:

$$(w^*_{i_1,1} - w_{i_1,2}) - (w^*_{i_0,2} - w_{i_0,2}) = w^*_{i_1,1} - w^*_{i_1,2} \geq 0$$

which must be positive given that individual i_1 chooses 1 over 2. As both losses are negative, this means that $\left|w^*_{i_1,1} - w_{i_1,2}\right| < \left|w^*_{i_0,2} - w_{i_0,2}\right|$ i.e. the mover loses less than the stayer.

Similarly, let individual i_3 be an 'upward' mover and individual i_2 be a stayer. The difference between the loss of i_3 and that of i_2 is given by $(w^*_{i_3,3} - w_{i_3,2}) - (w^*_{i_2,2} - w_{i_2,2})$. Using (A1), we have that:

$$(w^*_{i_3,3} - w_{i_3,2}) - (w^*_{i_2,2} - w_{i_2,2}) = w^*_{i_3,3} - w^*_{i_3,2} \geq 0$$

which must be positive given that individual i_3 chooses 3 over 2. As both losses are negative, this means that $\left|w^*_{i_3,3} - w_{i_3,2}\right| < \left|w^*_{i_2,2} - w_{i_2,2}\right|$ i.e. the mover loses less than the stayer.

A2. Theoretical Appendix: Idiosyncratic shocks and the selection of movers

We follow Moretti and Wilson (2017) by introducing time-varying idiosyncratic preferences for locations, which generate a positive probability of moving out of the location even for workers far from the thresholds. Assume the utility of working in location *l* for individual *i* in *t* now also depends on an idiosyncratic location specific random shock ε_{ilt} such that $U_{ilt} = w_{lt} + \eta_l \alpha_i + \varepsilon_{ilt}$ where $w_{lt} = B_{lt} - \sigma \log L_{lt}$. We analyze here the selection patterns of downward-movers from location *l* to location *l-1*, i.e. we have $\eta_l > \eta_{l-1}$. The analysis of the selection of upward-movers towards a location with higher returns to skills is symmetrical.

Denote by *M* the random event of moving, by $\bar{M}$ the complementary event of staying, and by $P(M \mid \alpha_i)$ the probability for individual *i* of moving from location *l* to location *l-1* conditional on α_i. From (1), omitting the time subscript for simplicity, we have

$$\begin{aligned} P\left(M \mid \alpha_i\right) &= P\left(U_{il} < U_{i,l-1}\right) = P\left(w_{lt} - w_{l-1} + (\eta_l - \eta_{l-1})\alpha_i < \varepsilon_{il-1} - \varepsilon_{il}\right) \\ &= 1 - F_{\Delta\varepsilon}\left(w_l - w_{l-1} + (\eta_l - \eta_{l-1})\alpha_i\right) \end{aligned}.$$

where $F_{\Delta\varepsilon}$ denotes the cumulative distribution function of $\Delta\varepsilon = \varepsilon_{il-1} - \varepsilon_{il}$. The conditional probability of moving is strictly decreasing in α_i as

$\dfrac{\partial P(M \mid \alpha_i)}{\partial \alpha_i} = -(\eta_l - \eta_{l-1}) f_{\Delta\varepsilon}(w_l - w_{l-1} + (\eta_l - \eta_{l-1})\alpha_i) < 0$ where $f_{\Delta\varepsilon}$ is the pdf of $\Delta\varepsilon$.

We first analyze the selection of movers. The average level of ability in the location is given by $E(\alpha_i) = \sum_{\alpha_i \in [v_{s-1}; v_s]} \alpha_i f(\alpha_i)$ where $f(\alpha_i) = P(\alpha = \alpha_i \mid i \in l)$ is the probability mass function of α_i in location *l* whereas v_{l-1} and v_l are the ability thresholds governing the equilibrium allocation. The average ability of movers is denoted by $E(\alpha_i \mid M)$ and by definition is equal to $E(\alpha_i \mid M) = \sum_{\alpha_i \in [v_{l-1}; v_l]} \alpha_i f(\alpha_i \mid M)$ where $f(\alpha_i \mid M) = P(\alpha_i \mid M)$ is the probability mass function of α_i conditional on moving. Using Bayes' theorem, we can rewrite $E(\alpha_i \mid M) = \sum_{\alpha_i \in [v_{l-1}; v_l]} \alpha_i \frac{f(\alpha_i) P(M \mid \alpha_i)}{P(M)}$ where $P(M) = \sum_{\alpha_i \in [v_{l-1}; v_l]} f(\alpha_i) P(M \mid \alpha_i)$ is the unconditional probability of moving. Rearranging the previous expression, the relation between the conditional and unconditional expectation can be expressed as

$$E(\alpha_i \mid M) - E(\alpha_i) = \frac{\mathrm{Cov}(\alpha_i, P(M \mid \alpha_i))}{P(M)}. \quad \text{(A3)}$$

Since $P(M \mid \alpha_i)$ is strictly decreasing in α_i, then $\mathrm{Cov}(\alpha_i, P(M \mid \alpha_i)) < 0$ and the average ability of movers is smaller than the average ability in the population whereas the reverse holds for stayers. Formally, this implies that $E(\alpha_i \mid M) < E(\alpha_i) < E(\alpha_i \mid \bar{M})$.

We now analyze how a decline in w_l to w_l^* due to an immigration shock alters the selection of movers. Initially, the resulting fall in the wage in location *l* raises the threshold from v_{l-1} to v_{l-1}^*, which results in a probability of moving equal to one for individuals with ability within $[v_{l-1}, v_{l-1}^*]$. Denoting by M^* the random event of moving after the migration shock, we thus have $P(M^* \mid \alpha_i) = 1$ for all i such that $\alpha_i \in [v_{l-1}, v_{l-1}^*]$. For those individuals above the threshold, the probability to move also increases because wages are now lower in location l relative to $l-1$ and $P(M^* \mid \alpha_i) = 1 - F_{\Delta\varepsilon}(w_l^* - w_{l-1} + \alpha_i(\eta_l - \eta_{l-1}))$ for all i such that $\alpha_i \in [v_{l-1}^*, v_l]$. Since $w_l^* < w_l$ then $P(M^* \mid \alpha_i) > P(M \mid \alpha_i)$ for all α_i in location l and as a consequence $P(M^*) > P(M)$.

From (A3), the effect of a change in wages in location l on the average ability of movers is given by

$$E(\alpha_i \mid M) - E(\alpha_i \mid M^*) = \frac{\mathrm{Cov}(\alpha_i, P(M \mid \alpha_i))}{P(M)} - \frac{\mathrm{Cov}(\alpha_i, P(M^* \mid \alpha_i))}{P(M^*)}.$$

Rearranging the previous expression, it can be shown that its sign is equal to the sign of

$$P(M^*)E(\alpha_i P(M \mid \alpha_i)) - P(M)E(\alpha_i P(M^* \mid \alpha_i)).$$

As $P(M^*) > P(M)$ and, its sign is ambiguous. Intuitively, the change in the relative wage has two opposite effects on the selection of movers: first, the increase in the threshold *raises* the negative selection of movers as those below the threshold move with probability one. However, depending on the parameters value, this increase might be compensated by an increase in the probability to move for those above the threshold, which *lowers* in the negative selection of movers.

A3. Data Appendix

Occupation classification: The DADS panel contains information at the two-digit level on 27 different occupations before 1983 and 36 occupations from 1984-2007. Our baseline occupation groups are defined using the French Statistics Institute (INSEE)'s *catégories socio-professionnelles* which exclude independent workers and defines 4 one-digit level occupations: Managers (*Cadres et professions intellectuelles supérieures*), Technicians (*Professions intermédiaires*), Office clerks (*Employés*) and Blue-collar workers (*Ouvriers*). The group of "skilled blue-collar workers" includes skilled manufacturing blue-collar workers (*Ouvriers qualifiés de type industriel*), skilled craftsman (*Ouvriers qualifiés de type artisanal*), drivers (*Chauffeurs*) and skilled maintenance, warehousing and transportation blue-collar workers (*Ouvriers qualifiés de la manutention, du magasinage et du transport*). The group of "unskilled blue-collar workers" includes unskilled manufacturing blue-collar workers (*Ouvriers non-qualifiés de type industriel*), unskilled craftsman blue-collar worker (*Ouvriers non-qualifiés de type artisanal*), agricultural workers (*Ouvriers agricoles*).

Wage data: We aggregate job spells over the year to obtain the total annual labor earnings and number of days worked for each individual. Individuals that have worked in several occupations in a given year are allocated to the occupation held for the longest period of time. Daily wages are defined as total annual wages over the annual number of days worked. Residual wages are obtained by regressing separately at the commuting-zone level for each occupation group and census year the log daily wages on a set of twenty-five age fixed effects. Our final wage measure is the average change in the residual log daily wage between two censuses. To reduce the influence of outliers, we drop the bottom and top percentile of the change in residual log daily wages within each group in each census year.

Alignment of census and DADS data: Census data are available in 1968, 1975, 1982, 1990, 1999 and 2007. The DADS data is available on an annual basis from 1976 to 2007, except in 1981, 1983 and 1990 where the data were not collected. The 1982, 1999, and 2007 Census data are matched with the DADS from the same year. The Census data from 1975 and 1990 are matched with the DADS data from respectively 1976 and 1991.

Evolution of covered sectors in the DADS panel:
The sample always includes all private sector employees from 1976 to 2007 except for those in the agricultural sector. Self-employed workers are not included in the sample. Civil servants account for 20% of total employment in France and are progressively covered in the sample from 1984 with the inclusion of public sector hospitals (about 4% of total employment). However, the inclusion of other local and national civil servants (16% of total

employment) was only completed at the end of the 1990s. The employees of several large public firms (such as France Telecom or EDF) were also added progressively to the sample during the same period.

Commuting zones: Commuting zones are defined in a consistent way over time using the municipality identifier. We use the 2010 definition of commuting zones constructed by INSEE which includes 322 commuting zones. We drop 25 commuting zones in French overseas territories and in Corsica (less than 0.3% of the population) as a change in the department code in 1976 complicates their matching across datasets over time. We also drop 11 very small commuting zones with less than 50,000 inhabitants accounting for less than 0.8% of observations. Specifically, we drop commuting zones 4101 Longwy, 4111Thionville, 5214 Sablé-sur-Sarthe, 5316 Fontenay-le-Comte, 7206 Pauillac, 8306 Saint-Flour, 8307 Brioude, 9306 Menton - Vallée de la Roya, 9109 Clermont-l'Hérault – Lodève, 9110 Ganges, and 9116 Prades. As a result, our final sample consists of 286 commuting zones.

Regions: We use the contemporary definition of regions in France that includes 13 regions. After excluding the smallest region (Corsica), we end up exploiting 12 regions.

Housing cost data: We use data on local average rents at the municipality level from CLAMEUR (an observatory of housing prices financed by real-estate firms) collected by Chapelle and Eyméoud (2018) for the year 2007 that we completed manually for the year 2000, the first year with available data. The data provides average rent indexes calculated from real estate agents and administrative records for large municipalities and regions. When no municipality from the commuting zone was observed in the CLAMEUR sample, which might happen when both the municipality and its commuting zone are small, we follow Chapelle and Eyméoud (2018) and use rent data collected by them from ads posted in local newspapers and housing websites. Each commuting-zone price index is constructed as the weighted average of prices across its municipalities, with each municipality weighted by its population in 1999. The local price index is constructed by normalizing the 2007 index to 100.

Figures and Tables

Figure 1: Effect of Immigration on Workers assignment with Comparative Advantage

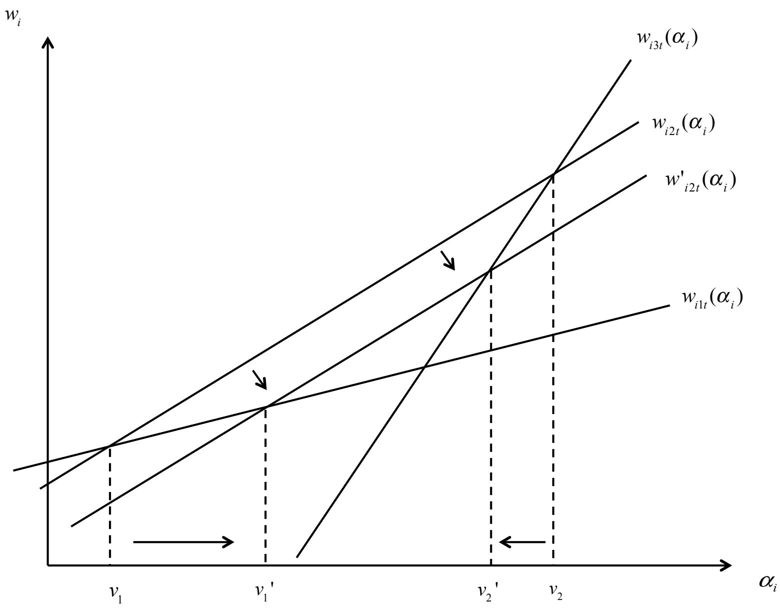

Table 1: Immigration in France, 1975-2007

	1975-82	1982-90	1990-99	1999-2007
Immigrant share in population	7.4	7.3	7.4	9.1
Share of recent arrivals in the population	1.30	1.17	1.20	2.3
	Distribution of recent arrivals by geographical origin			
Europe	27.2	30.7	42.0	31.7
Maghreb	31.4	23.1	22.1	28.3
Sub-Saharan Africa	11.0	14.7	13.9	17.5
Asia	25.4	24.4	15.3	15.5
Other	5.0	7.1	6.7	7.0
	Serial correlation in the immigrant inflow rates across commuting zones			
$corr(\Delta p_{lt}, \Delta p_{lt-1})$	0.16	0.42	0.53	0.48
$corr(\Delta p_{lt}, \Delta p_{lt-2})$	na	0.50	0.36	0.44
	Serial correlation of past settlement IV for the immigrant inflow rates (fixed base period in 1975)			
$corr(\Delta \tilde{p}_{lt}^{75}, \Delta \tilde{p}_{lt-1}^{75})$	0.57	0.92	0.69	0.72
$corr(\Delta \tilde{p}_{lt}^{75}, \Delta \tilde{p}_{lt-2}^{75})$	n.a.	0.46	0.62	0.25

Sources: 1968, 1975, 1982, 1990, 1999 and 2007 Census data. Calculations from the authors. Notes: The sample includes 286 commuting zones. Recent arrivals are defined as immigrants present in Census *t* but not in Census *t-1*. The immigrant inflow rate is the change in the number of employed immigrants between censuses divided by the initial total number of employees in the commuting zone. The past settlement IV predicts changes in the immigrant inflow rate by combining inflows at the national level with differences in settlement patterns in 1975 for 54 immigration groups.

Table 2: Immigration across Regions and Occupations

A. Percentage share of recent arrivals of immigrants in the population of France and 12 French regions				
	1975-82	1982-90	1990-99	1999-2007
France	1.30	1.17	1.19	2.02
Paris (Île-de-France)	2.88	2.72	2.51	3.95
Grand Est	1.17	0.99	1.27	1.90
Nouvelle-Aquitaine	0.66	0.63	0.74	1.62
Auvergne-Rhône-Alpes	1.26	1.06	1.10	2.00
Bourgogne-Franche-Comté	1.00	0.66	0.71	1.31
Bretagne	0.29	0.37	0.46	1.07
Centre-Val de Loire	0.99	0.76	0.62	1.33
Occitanie	1.13	1.09	1.26	2.01
Hauts-de-France	0.67	0.56	0.51	1.00
Normandie	0.60	0.51	0.47	0.95
Pays de la Loire	0.40	0.34	0.45	1.03
Provence-Alpes-Côte d'Azur (PACA)	1.61	1.38	1.38	2.11
B. Percentage share of foreign-born across occupations, 1982-2017, males aged 25-55				
	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
1982	9.9	9.1	15.9	17.6
1991	12.4	9.5	14.3	16.8
1999	12.1	8.7	12.8	15.6
2007	11.3	8.4	13.4	18.3
C. Distribution across occupations in 2007 for males aged 25-55 (percentage)				
Natives	20.4	22.7	42.8	14.0
Foreign born	18.0	14.4	45.9	21.7

Sources: Panel A: 1968, 1975, 1982, 1990, 1999 and 2007 Census data, Panel B and C: DADS data. Calculations from the authors. Notes: Recent arrivals are defined as immigrants present in France in Census *t* but not in Census *t-1*. The share of recent arrivals is the number of recent arrivals divided by the initial population of the region (in percentage terms).

Table 3: First Stage Regressions

Dependent variable: *Immigrant inflows* Δp_{lt}						
Panel A: Stacked first differences 1975-2007						
Instrument definition	$\Delta\tilde{p}_{lt}^{75}$ base period $t_0 = 1975$			$\Delta\tilde{p}_{lt}^{t-2}$ base period: $t_0 = t-2$		
	(1)	(2)	(3)	(4)	(5)	(6)
Past settlement instrument	0.458***	0.411***	0.391***	0.619***	0.568***	0.557***
	(0.074)	(0.082)	(0.103)	(0.080)	(0.083)	(0.102)
Lagged past settlement instrument			0.026			0.014
			(0.065)			(0.074)
First Stage F-stat	38.4	24.2	12.9	58.3	45.6	22.8
N	1144	1144	1144	1144	1144	1144
Region fixed effects	No	Yes	Yes	No	Yes	Yes

Panel B: Period by period first-differences				
	1975-82	1982-90	1990-99	1999-2007
1. Past settlement instrument $\Delta\tilde{p}_{lt}^{75}$ base period $t_0 = 1975$ with its lag				
Past settlement instrument	0.307***	0.579	0.194	0.290*
	(0.116)	(0.468)	(0.146)	(0.156)
Lagged past settlement instrument	0.095	0.145	0.176*	0.057
	(0.115)	(0.542)	(0.097)	(0.126)
First Stage F-stat	11.8	23.3	11.5	2.8
2. Past settlement instrument $\Delta\tilde{p}_{lt}^{t-2}$ base period $t_0 = t-2$ with its lag				
Past settlement instrument	0.370***	0.579	0.459**	0.753***
	(0.104)	(0.468)	(0.184)	(0.194)
Lagged past settlement instrument	0.084	0.145	0.179	-0.067
	(0.109)	(0.542)	(0.138)	(0.163)
First Stage F-stat	16.1	23.3	14.2	12.6
N	286	286	286	286

Sources: 1968, 1975, 1982, 1990, 1999 and 2007 Census data. Notes: The table shows regression results where the dependent variable is the immigrant inflow rate defined as the increase in labor supply due to immigration in the commuting zone between censuses. The independent variables are the past settlement shift-share instrument base period 1975 or base period *t-2*. Regressions are estimated using 286 commuting zones and changes in the immigration ratio over 1975-82, 1982-90, 1990-99, 1999-2007. Panel A shows stacked first-differences. Panel B shows each first-difference separately. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, and the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 4: Impact of Immigration on Native Outflows from Commuting Zones, 1975-2007

Dependent variable: *Adjusted probability to work in a different commuting zone between two consecutive Census years*					
	OLS Estimates				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
	Sample group under consideration among male workers 25-50 in first period				
	A. OLS Estimates				
Immigrant inflow	0.359***	0.175	0.223*	0.377***	0.378***
	(0.091)	(0.164)	(0.122)	(0.098)	(0.103)
	B. 2SLS Estimates with instrument base period 1975				
Immigrant inflow	0.790**	0.810	0.903**	0.829**	0.652
	(0.332)	(0.709)	(0.410)	(0.361)	(0.426)
N	1144	1144	1144	1144	1144
First Stage F-stat	24.2	24.2	24.2	24.2	24.2
	C. 2SLS Estimates allowing for selection				
Immigrant inflow	0.800**	-0.316	0.883*	1.638***	1.001*
	(0.367)	(1.022)	(0.534)	(0.450)	(0.512)
Rank wage(t-1) x Immigrant inflow	-0.017	2.402*	0.047	-1.618***	-0.738
	(0.302)	(1.378)	(0.625)	(0.523)	(0.785)
Rank wage(t-1)	0.027***	0.056***	0.035***	-0.091***	-0.132***
	(0.005)	(0.018)	(0.009)	(0.006)	(0.008)
N	677,740	87,381	241,203	253,891	95,265
First Stage F-stat	12.4	12.6	12.5	12.4	12.4
Baseline rate	22.7	31.3	25.8	18.0	19.3
Share in group	100%	13%	36%	37%	14%
Predicted effects of a 1 p.p. increase in immigrant inflow by initial rank (in p.p.) (in italic if not significant at the 10% level)					
Native initially at the top (rank 1)	0.78	2.06	0.94	*0.02*	*0.26*
Native initially at the bottom (rank 0)	0.80	*-0.32*	0.88	1.64	1.00
Difference (top – bottom)	*-0.02*	2.38	*0.04*	-1.62	*-0.74*

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show estimates of regressions where the dependent variable is the age-adjusted probability for a native worker to work by census *t* in a commuting zone different from the one in which he was working in census *t-1*. Each column reports estimates of the model on a different group of workers defined by their initial occupation and commuting zone in *t-1*. Panel A and B show regressions using commuting zone averages, whereas Panel C shows regressions at the individual level. The models are estimated with OLS in panel A and with 2SLS in Panels B and C. Regressions in Panel C are weighted using the inverse of the number of observations per commuting zone. The instruments are the past settlement base period 1975 and its interaction with the initial wage rank in Panel C. All regressions include a full set of region and time fixed-effects and their interaction with the start-of-period log number of employees, and the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in the immigration ratio in the origin commuting zone over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 5: Differences in the Characteristics of the Origin and Destination Commuting Zones for Observed Commuting-Zone Moves

	Sample group of movers under consideration among male workers 25-50 in first period				
	All movers	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue collars
A. Dependent variable: *Differences in immigrant ratio*: $p_{dt} - p_{ot}$, 1975-2007					
Immigrant inflow	-0.112**	-0.160***	-0.122**	-0.125***	-0.064
	(0.045)	(0.052)	(0.049)	(0.042)	(0.047)
N	153,457	27,354	62,054	45,763	18,434
First Stage F-stat	24.2	24.2	24.2	24.2	24.2
B. Dependent variable: *Differences in immigrant inflows*: $\Delta p_{dt} - \Delta p_{ot}$, 1975-2007					
Immigrant inflow	-0.722***	-0.848***	-0.711***	-0.730***	-0.739***
	(0.084)	(0.084)	(0.086)	(0.099)	(0.092)
N	153,457	27,354	62,054	45,763	18,434
First Stage F-stat	24.2	24.2	24.2	24.2	24.2
C. Dependent variable: *Differences in log rent index between destination and origin commuting zone*, 1999-2007					
Immigrant inflow	-2.124**	-3.104***	-2.328***	-2.051**	-1.896**
	(0.869)	(1.043)	(0.899)	(0.891)	(0.930)
N	56,710	10,845	23,484	16,465	5,958
First Stage F-stat	22.4	22.4	22.4	22.4	22.4

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data, and data on rents at the commuting zone level obtained from Chapelle and Eyméoud (2018). Notes: This table shows regression estimates for alternative measures of the differences in the characteristics of the origin (*o*) and destination (*d*) commuting zones for all the observed natives that move to work in a different commuting zone between two census years. Regressions are weighted using the inverse of the number of observations per commuting zone. Whereas movers are observed between census year *t-1* and *t*, the differences in origin and destination are measured in the census year *t* for both commuting zones. For all the regressions, the independent variable is the immigrant inflow in the origin commuting zone. The dependent variable in Panel A is the difference in the immigrant ratio. The dependent variable in Panel B is the difference in immigration inflows. In Panel C, the dependent variable is the difference in the log rent index. Regressions are estimated using 286 commuting zones and changes in immigration ratio over 1975-82, 1982-90, 1990-99, 1999-2007 and include region fixed effects. Panel A and B use stacked first-differences, whereas panel C uses the 1999-2007 first-difference. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level. The first stage F-stat is the Kleibergen-Paap rk Wald F statistic.

Table 6: Impact of Immigration on Native Inflows and Population in Commuting Zones, 1975-2007

	Sample group under consideration among male workers 25-50 in th first period				
	(1)	(2)	(3)	(4)	(5)
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
Dependent variable: *inflows into the group in the commuting zone between two consecutive censuses*					
	A. OLS Estimates				
Immigrant inflow	0.450***	0.599**	0.365***	0.370***	0.121
	(0.087)	(0.249)	(0.118)	(0.069)	(0.126)
N	1144	1144	1144	1144	1144
	B. 2SLS Estimates with instrument base period 1975				
Immigrant inflow	-0.161	0.500	0.062	-0.463**	-0.773***
	(0.193)	(0.553)	(0.319)	(0.211)	(0.287)
N	1144	1144	1144	1144	1144
First Stage F-stat	24.2	24.2	24.2	24.2	24.2
	C. 2SLS Estimates allowing for selection				
Immigrant inflow	-0.029	0.340	0.710	-0.290	-1.602
	(0.217)	(1.022)	(0.635)	(0.228)	(1.192)
Rank wage(t-1) x Immigrant inflow	-0.116	0.086	-0.523	-0.136*	1.058
	(0.078)	(1.130)	(0.412)	(0.081)	(0.999)
Rank wage(t-1)	-0.001	-0.013	-0.002	-0.003***	-0.011*
	(0.001)	(0.016)	(0.003)	(0.001)	(0.006)
N	677,740	87,381	241,203	253,891	95,265
First Stage F-stat	12.4	12.6	12.5	12.4	12.4
Baseline rate	22.7	31.3	25.8	18.0	19.3
Share in group	100%	13%	36%	37%	14%
Predicted effects of a 1 p.p. increase in immigrant inflow by initial rank (in p.p.) (in italic if not significant at the 10% level)					
Native initially at the top (rank 1)	*-0.15*	*0.43*	*0.19*	*-0.43*	*-0.54*
Native initially at the bottom (rank 0)	*-0.03*	*0.34*	*0.71*	*-0.29*	*-1.60*
Difference (top – bottom)	*-0.12*	*0.09*	*-0.52*	*-0.14*	*1.06*
Dependent variable: *growth of the population of native employees*					
	D. 2SLS Estimates				
Immigrant inflow	-0.951**	-0.310	-0.841*	-1.289***	-1.425***
	(0.384)	(0.899)	(0.519)	(0.418)	(0.513)
N	1144	1144	1144	1144	1144
First Stage F-stat	24.2	24.2	24.2	24.2	24.2

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: Panels A to C show regression results at the commuting zone level where the dependent variable is the share of native employees joining the commuting zone to work within each specified occupation between census *t-1* and *t*. Panel D shows regression results at the commuting zone level where the dependent variable is the total native population in the group. The models are estimated with OLS in Panel A and by 2SLS in Panel B, C and D. The instruments for changes in immigration ratio in Panel B, C and D is the past settlement instrument base period 1975 and its interaction with the initial wage rank in panel C. Regressions in panel C are weighted using the inverse of the number of observations per commuting zone. All regressions include a full set of region and time fixed effects and their interaction with the start-of-period share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 7: Impact of Immigration on Log Daily Wages

	Sample group under consideration among male workers, 25-50 in first-period.				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
Dependent variable: *Change in the average log residual daily wage in the commuting zone*					
	1. Estimates using current location				
	A. OLS Estimates using current location				
Immigrant inflow	0.261***	0.138	0.216**	0.123	0.081
	(0.069)	(0.278)	(0.102)	(0.083)	(0.143)
	B. 2SLS Estimates using current location				
Immigrant inflow	0.258	-0.492	0.156	0.177	-0.431
	(0.174)	(0.860)	(0.264)	(0.209)	(0.478)
	2. Estimates using baseline location				
	C. OLS Estimates using baseline location				
Immigrant inflow	0.096***	-0.077	0.090	0.044	0.078
	(0.035)	(0.151)	(0.066)	(0.050)	(0.119)
	D. 2SLS Estimates using baseline location				
Immigrant inflow	-0.238*	0.134	-0.419*	-0.334***	-0.987**
	(0.121)	(0.545)	(0.215)	(0.128)	(0.482)
First Stage F-stat	38.4	38.4	38.4	38.4	38.4
N	1144	1144	1144	1144	1144

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census. Notes: The dependent variable is the change in the average log residual daily wage in the commuting zone. Estimates in Panel 1 are based on average wages computed using information on the current location (or location/occupation) of each native worker in each period. Estimates in Panel 2 are based on average wages computed using the baseline (first-period) location (or location/occupation) of each native worker. The sample in Panel 1 includes all workers initially observed in the occupation x commuting zone cell. The models are estimated with OLS in Panels A and C and with 2SLS in Panels B and D using the past settlement instrument base period 1975. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 8: Impact of Immigration on Log Annual Days Worked per worker

	Sample group under consideration among male workers, 25-50 in first-period.				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
Dependent variable: *Change in average residual log annual days worked per worker*					
	1. Estimates using current location				
	A. OLS Estimates using current location				
Immigrant inflow	0.033	0.006	-0.045	0.072	0.208
	(0.062)	(0.120)	(0.092)	(0.076)	(0.155)
	B. 2SLS Estimates using current location				
Immigrant inflow	-0.170	-0.145	-0.747**	0.299**	-0.166
	(0.164)	(0.513)	(0.310)	(0.175)	(0.534)
	2. Estimates using baseline location				
	C. OLS Estimates using baseline location				
Immigrant inflow	0.015	-0.035	0.013	0.021	-0.125
	(0.028)	(0.091)	(0.048)	(0.034)	(0.034)
	D. 2SLS Estimates using baseline location				
Immigrant inflow	-0.019	-0.624*	-0.163	0.124	0.111
	(0.123)	(0.366)	(0.181)	(0.141)	(0.328)
First Stage F-stat	38.4	38.4	38.4	38.4	38.4
N	1144	1144	1144	1144	1144
Share in group	100%	13%	36%	37%	14%

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census. Notes: The dependent variable is the change in average residual log annual days worked per worker in the commuting zone. Estimates in Panel 1 are based on average residual daily wages computed using information on the current location (or location/occupation) of each native worker in each period. Estimates in Panel 2 are based on average residual daily wages computed using the baseline (first-period) location (or location/occupation) of each native worker. The models are estimated with OLS in Panels A and C and with 2SLS in Panels B and D using the past settlement instrument base period 1975. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 9: Impact of Immigration on Log Annual wages

	Sample group under consideration among male workers, 25-50 in first-period.				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
Dependent variable*: Change in average residual log annual days worked per worker*					
	1. Estimates using current location				
	A. OLS Estimates using current location				
Immigrant inflow	0.293***	0.142	0.172	0.200	0.289
	(0.106)	(0.299)	(0.145)	(0.103)	(0.237)
	B. 2SLS Estimates using current location				
Immigrant inflow	0.090	-0.643	-0.586	0.053	-0.597
	(0.274)	(1.023)	(0.443)	(0.274)	(0.712)
	2. Estimates using baseline location				
	C. OLS Estimates using baseline location				
Immigrant inflow	0.129**	0.029	0.097	0.078	-0.107
	(0.051)	(0.193)	(0.088)	(0.077)	(0.206)
	D. 2SLS Estimates using baseline location				
Immigrant inflow	-0.171	-0.327	-0.548	-0.175	-0.888
	(0.206)	(0.695)	(0.351)	(0.201)	(0.586)
First Stage F-stat	38.4	38.4	38.4	38.4	38.4
N	1144	1144	1144	1144	1144
Share in group	100%	13%	36%	37%	14%

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census. Notes: The dependent variable is the change in average residual log annual wage per worker across commuting zones. Estimates in Panel 1 are based on average residual residual log annual wage computed using information on the current location (or location/occupation) of each native worker in each period. Estimates in Panel 2 are based on average residual log annual wages computed using the baseline (first-period) location (or location/occupation) of each native worker. The models are estimated with OLS in Panels A and C and with 2SLS in Panels B and D using the past settlement instrument base period 1975. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 10: Does the Impact of Immigration differ between Movers and Stayers?

	All employees		Managers		Technicians and clerks		Skilled blue-collars		Unskilled blue collars	
A. Dependent variable: *Average change in log residual daily wage*										
Immigrant inflow	-0.238*	-0.168	0.134	0.274	-0.419*	-0.252	-0.334***	-0.239*	-0.987**	-0.719*
	(0.121)	(0.129)	(0.545)	(0.612)	(0.215)	(0.171)	(0.128)	(0.132)	(0.482)	(0.390)
Immigrant Inflow x location shifter dummy		-0.290		-0.996		-0.628		-0.320		-1.151*
		(0.274)		(0.993)		(0.492)		(0.272)		(0.664)
Location shifter dummy		0.007**		-0.028**		0.015**		-0.007*		0.037***
		(0.004)		(0.013)		(0.007)		(0.004)		(0.008)
B. Dependent variable: *Average change in residual log annual days worked per worker*										
	All employees		Managers		Technicians and clerks		Skilled blue-collars		Unskilled blue collars	
Immigrant inflow	-0.019	-0.244***	-0.624*	-0.651	-0.163	-0.308*	0.083	-0.241*	0.111	-0.255
	(0.123)	(0.094)	(0.366)	(0.443)	(0.181)	(0.184)	(0.150)	(0.126)	(0.328)	(0.290)
Immigrant Inflow x location shifter dummy		0.759***		0.113		0.342		1.426***		1.084*
		(0.283)		(0.563)		(0.415)		(0.429)		(0.613)
Location shifter dummy		0.006		-0.010		0.021***		-0.017**		0.034***
		(0.004)		(0.009)		(0.007)		(0.007)		(0.011)
C. Dependent variable: Average change in residual log annual wage										
Immigrant inflow	-0.171	-0.434**	-0.327	-0.480	-0.548	-0.447	-0.175	-0.362*	-0.888	-1.144**
	(0.206)	(0.201)	(0.695)	(0.641)	(0.351)	(0.315)	(0.201)	(0.218)	(0.586)	(0.541)
Immigrant Inflow x location shifter dummy		0.869*		0.657		-0.492		1.640**		0.485
		(0.447)		(1.293)		(0.682)		(0.699)		(0.841)
Location shifter dummy		0.010		-0.056***		0.027**		-0.035***		0.071***
		(0.007)		(0.019)		(0.011)		(0.009)		(0.013)
N	677,723	677,723	87,358	87,358	241,117	241,117	253,891	253,891	95,265	95,265
First Stage F-stat	38.4	19.7	38.4	19.7	38.4	19.7	38.4	19.7	38.4	19.7
Period	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show individual level regression results where the dependent variable is the change between census year *t-1* and census year *t* in residual log daily wage for natives holding an unskilled blue-collar job in *t-1* in panel A, in residual annual days worked in panel B, in residual log annual wage in panel C. All regressions are weighted using the inverse of the number of workers initially in each commuting zone. The residual wages have been obtained in an individual-level regression on age dummies estimated separately on each census year and occupation group. The models are estimated with 2SLS using the past settlement instrument base period 1975 for the change in the immigration ratio. We also use as instruments the interaction between the past settlement instrument with the location shifter dummy when the interaction term is included in the model. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Locations are defined using the initial location across 286 commuting zones and changes in immigration ratio are measured over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 11: Adjusting wages for differences in housing costs across commuting zones

Dependent variable: *Change in log residual daily wages between t-1 and t* 2SLS estimates using the baseline location						
	Skilled blue-collar			Unskilled blue-collar		
	Adjustments for housing costs 1999-2007			Adjustments for housing costs 1999-2007		
	None	20% housing share	30% housing share	None	20% housing share	30% housing share
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant inflow	-0.254	-0.706**	-0.938***	-0.153	-0.581	-0.768
	(0.218)	(0.299)	(0.363)	(0.633)	(0.567)	(0.675)
Immigrant Inflow x location shifter dummy	-0.675*	0.018	0.399	-0.266	0.370	0.728
	(0.351)	(0.321)	(0.349)	(0.884)	(0.917)	(0.946)
Location shifter dummy	0.010	-0.015**	-0.029***	0.014	-0.012	-0.024
	(0.008)	(0.008)	(0.008)	(0.019)	(0.020)	(0.020)
N	76,255	76,255	76,255	23,989	23,989	23,989
First Stage F-stat	5.5	5.5	5.5	5.5	5.5	5.5
Period	1999-2007	1999-2007	1999-2007	1999-2007	1999-2007	1999-2007

Sources: Data are from the DADS panel 1999-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show individual level regression results where the dependent variable is the change between census year *t-1* and census year *t* in residual log daily wages for natives holding an unskilled blue-collar job in *t-1*. All regressions are weighted using the inverse of the number of workers initially in each commuting zone. The residual wages have been obtained in an individual-level regression on age dummies estimated separately on each census year and occupation group. The models are estimated with 2SLS using the past settlement instrument base period 1975 for the change in the immigration ratio. We also use as instruments the interaction between the past settlement instrument with the location shifter dummy when the interaction term is included in the model. We focus on the 1999-2007 first differences and adjust residual wages using a constructed local price index where housing accounts for respectively 20% and 30% of total spending in columns 2 and 3 and 5 and 6. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Locations are defined using the initial location across 286 commuting zones and changes in immigration ratio are measured over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 12: Robustness to Sample Attrition

	Sample group under consideration among Male workers 25-50 in first-period 2SLS estimates using the baseline location				
	All employees	Managers	Technicians and clerks	Skilled blue-collar	Unskilled blue-collar
	A. Dependent variable: Change in log of the 3-year average of daily wages around census years, imputing zero wages when missing				
Immigrant inflow	-0.273***	-0.172	-0.205	-0.380***	-0.973**
	(0.100)	(0.454)	(0.161)	(0.107)	(0.301)
	B. Median change in log daily wage, no imputation				
Immigrant inflow	-0.203*	-0.477	-0.358**	-0.105	-0.765**
	(0.115)	(0.505)	(0.141)	(0.198)	(0.374)
	C. Median change in log daily wage, impute zero wage if missing				
Immigrant inflow	-0.356***	0.931	-0.543	-0.175	-0.897
	(0.134)	(1.319)	(0.378)	(0.589)	(0.655)
	D. Median change in log daily wage, impute last observed wage if missing				
Immigrant inflow	-0.257**	0.162	-0.458*	-0.201	-0.943*
	(0.131)	(0.631)	(0.244)	(0.219)	(0.534)
N	1144	1144	1144	1144	1144
First Stage F-stat	37.2	37.2	37.2	37.2	37.2
Share in group	100%	13%	36%	37%	14%

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: Panel A shows regression results where the dependent variable is the change in average log residual daily wages across commuting zones calculated over three years and imputing zero when one year is missing from the sample for an individual. Panel B shows the baseline estimates using the median change in log daily wages. In Panel C, we include workers observed in *t-1* but with missing observation in period *t* in the sample by imputing a log daily wage of zero. In Panel D, we include these workers by imputing the previous observed residual wage in the sample. The residual wages have been age adjusted from an individual-level regression on age dummies estimated separately on each census year and occupation group. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, and with the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using the initial location and occupation across 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table 13: Robustness to alternative Specifications, 2SLS Estimates

Sample: Male skilled blue-collar workers 25-50 in first-period.

	(1)	(2)	(3)	(4)
	Benchmark	Instrument base period *t-2*	Controlling for lagged inflows	Commuting zone fixed effect (286 CZ)
A. Dependent variable: *Adjusted probability to leave the commuting zone*				
Immigrant inflow	1.638***	1.818***	2.057***	0.948***
	(0.450)	(0.378)	(0.465)	(0.331)
Rank wage(t-1) x Immigrant inflow	-1.618***	-1.622***	-2.110***	-1.638***
	(0.523)	(0.371)	(0.421)	(0.535)
Rank wage(t-1)	-0.091***	-0.091***	-0.095***	-0.090***
	(0.006)	(0.006)	(0.006)	(0.006)
Lagged immigrant inflow			0.171	
			(0.286)	
Rank wage(t-1) x lagged immigrant inflow			0.865	
			(0.974)	
Test absence first-order serial correlation (p-value)	6.4 (p=0.00)	6.1 (p=0.00)	12.0 (p=0.00)	-5.1 (p=0.00)
Test absence second-order serial correlation (p-value)	5.8 (p=0.00)	4.9 (p=0.00)	7.3 (p=0.00)	-4.6 (p=0.00)
N	253,891	253,891	253,891	253,891
First Stage F-stat	12.4	23.4	11.5	13.0
B. Dependent variable: *Inflow into the skilled blue-collar occupations*				
Immigrant Inflow	-0.463**	-0.239**	-1.257**	-0.390
	(0.211)	(0.182)	(0.595)	(0.373)
Lagged immigrant inflow			1.049**	
			(0.528)	
Test absence first-order serial correlation (p-value)	-5.49 (p=0.00)	-4.46 (p=0.00)	-5.88 (p=0.00)	-7.88 (p=0.00)
Test absence second-order serial correlation (p-value)	-0.30 (p=0.76)	0.38 (p=0.70)	-0.79 (p=0.42)	-2.58 (p=0.01)
C. Dependent variable: *Average change in log residual daily wages*				
Immigrant inflow	-0.334***	-0.239**	-0.397	-0.032
	(0.128)	(0.102)	(0.247)	(0.196)
Lagged immigrant inflow			0.061	
			(0.185)	
Test absence first-order serial correlation (p-value)	-1.78 (p=0.08)	-2.00 (p=0.05)	-1.76 (p=0.08)	-7.57 (p=0.00)
Test absence second-order serial correlation (p-value)	0.20 (p=0.84)	0.13 (p=0.89)	0.27 (p=0.79)	-5.01 (p=0.00)
N	1144	1144	1144	1144
First Stage F-stat	38.4	58.3	11.0	19.0

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: The dependent variable in Panel A is the adjusted probability to leave his initial commuting zone, the inflow rate in panel B and the average change in the residual log daily wages in Panel C for a balanced sample of workers initially in the location and occupation. The residual wages have been obtained in an individual-level regression on age dummies estimated separately on each census year. The estimation method is 2SLS using the past settlement instrument base period 1975 for the change in the immigration ratio, except in column 2 where the base year *t-2* is used instead. Column 3 includes the lagged shift-share as an additional instrument. Column 1 reproduces for convenience in respectively Panel A and B the results presented in Panel B of Table 5 and Panel C of Table 7. Column 3 controls for lagged immigration inflows. Column 4 includes fixed effects for commuting zones. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using the initial occupation and location across 286 commuting zones and changes in immigration ratio over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Online Appendix: Who Stays and Who Leaves? Immigration and the Selection of Natives across Locations

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A1. Determinants of Attrition

We test in Table A4 whether attrition is related to commuting zone level increases in labor supply due to immigration by showing regressions in which the dependent variable is the probability to be missing in census year *t* in the DADS sample conditional on having been observed in census year *t-1*. Panel A, that reports simple commuting zone level regressions, shows there is no significant correlation between the aggregate attrition rates and immigrant inflows. In Panel B, we additionally control for differences in observable characteristics of workers across commuting zones using individual level data. Whereas workers initially working full time and having higher wages are more likely to be observed in the next period, there is no statistically significant effect of immigration on the probability of attrition.

A2. Short- and Long-Run Adjustment

Does the negative effect of immigration on wages persist over time? Thanks to the long-time span covered by our data (1976-2007), we can use long-differences specifications using changes over 15 to 17 years to test whether wages are affected by distant immigration shocks, and this while accounting for compositional changes that are likely to be even more important in the longer run. Note that the "long-term" immigrant inflow between censuses *t* and *t-2*, denoted by $\Delta p_{lt/t-2} = (I_{l,t} - I_{l,t-2}) / L_{l,t-2}$ can be decomposed as $\Delta p_{lt/t-2} = \Delta p_{lt/t-1} + \Delta p_{lt-1/t-2}$ where $\Delta p_{lt/t-1} = (I_{l,t} - I_{l,t-1}) / L_{l,t-2}$ and $\Delta p_{lt-1/t-2} = (I_{l,t-1} - I_{l,t-2}) / L_{l,t-2}$ are respectively the recent and distant increases in labor supply due to immigration. Using this decomposition, we estimate the model:

$$w_{lt}^{k} - w_{lt-2}^{k} = \gamma_{kt} + \beta_{Rk} \Delta p_{lt/t-1} + \beta_{Dk} \Delta p_{lt-1/t-2} + \mathbf{X}_{lt-2}^{'} \varphi_{kt} + \varepsilon_{lt}^{k}$$

where $w_{lt}^{k} - w_{lt-2}^{k}$ is the "long-difference" change in wages. If immigration decreases wages permanently, then we should have $\beta_{Rk} = \beta_{Dk}$. If the effects are temporary, then only recent shocks should have a negative effect on contemporary wages.

The results in Appendix Table A5 show that whereas the coefficients of recent immigrant increases in labor supply are negative --and statistically significant for unskilled blue-collar workers, the coefficient for distant increases is instead positive for most groups, although statistically significant only for managers. Overall, consistent with Monras (2018) and Jaeger et al. (2018), this result implies that immigration shocks are not persistent and that wage losses induced by immigration are temporary. However, the results must be interpreted with caution as the first-stage F-stat are rather low.

A3. Are occupations the most relevant dimension?

So far, our approach has been to define groups of natives on the basis of their initial occupation. However, it might be equivalent and simpler to focus on those having a low wage, rather than belonging to specific occupations. To investigate the importance of isolating specific occupations, we report in Appendix Table A6 estimates of the average impact of immigration for natives belonging to the first and to the second quartiles of the initial location's residual wage distribution. We find that immigration has no statistically significant effect on average wages in each quartile. In contrast, when the effect is allowed to vary with the initial occupation, we find a strong negative impact on the wage of blue-collar workers, with effects that are particularly large for the unskilled blue-collars. These results confirm that the initial occupational affiliation is an important dimension in identifying those workers most affected by immigration, at least in the French context, as reported earlier by Cohen-Goldner and Paserman (2011) and De New and Zimmermann (1994).

A4. Heterogeneity by Initial Industry

In Table A9, we study whether the effects of immigration on wages depend on the initial industry of the worker. In Column 3, we test whether the effects of immigration vary with the industry of origin of the worker by distinguishing three groups of industries: the tradable sector, which serves as a reference, the non-tradable sector and the construction sector. Clearly, the effects of immigration on wages vary widely with the industry of origin of the worker: for both skilled and unskilled blue-collar workers, the negative effects of immigration are much stronger in the non-tradable industries and the construction sector compared with the tradable sector. Overall, these results suggest that the impact of immigration might differ in important ways not only across occupation groups but also across industries.

Industry aggregations: Following Dustmann and Glitz (2015), the group of "tradable" industries includes manufacturing, agriculture, mining, finance and real estate. The group of "non-tradable" industries always includes transportation, hotels and restaurants, retail and wholesale trade, automobile repair and dealer but not the construction sector. We always consider separately the construction sector.

A5. Differences by age

The effects of immigration on mobility might vary with the age of the worker as residential mobility decreases with age. Immigrants might also be more in competition with younger workers that have less experience. We test for differences between age groups in response to immigration in Appendix Table A10 using estimates where we have introduced two interaction terms between immigration and the initial age group of the worker in the first period of each first-difference regression. Using the 25-34 age group as a reference, the estimated coefficients of the interaction terms indicate whether the effects of immigration differ for workers initially aged 35-44 and 45-50 in the first period of each first difference.

For the probability to change the commuting zone of the job, the results reported in Panel A are consistent with the hypothesis that immigration has a lower effect on workers over 35, in particular for technicians and clerks. However, the differences are not statistically significant except for managers and technicians.

In Panels B and C, we investigate differences by age in the effect of immigration on daily wages and the annual number of days worked. We find some evidence of a more negative effect of immigration on these outcomes for younger workers. However, once again, the differences are imprecise and are not statistically significant.

A6. Department level estimates

Until here, all the estimation results reported in the paper use the commuting zone as the geographical definition of local labor markets. In order to assess how our results are affected by this choice, we reproduce our main results using the more aggregated geographical level of the 93 French departments. For consistency, we use the department of the job and not of residence of native workers to estimate these models.

We reproduce our main analysis in appendix Tables A11, A12, and A13 for respectively inflows, outflows and wages. We observe lower effects of immigration on the probability to leave the department, except for blue-collar workers, while the effects of immigration on inflows of blue-collar workers are negative but statistically insignificant. The effects on wages are also negative but they tend to be more imprecise for daily wages.

A7. Change of residence or in commuting patterns?

One important issue for the interpretation of our results is that we measure mobility using changes in the commuting zone of the *job* between two census years, not in the *residence* of the worker. While the commuting zone of the job is the appropriate level to capture the relevant local labor market, a possibility is that immigration mostly affects commuting patterns and not the place of residence of the worker. Unfortunately, one limitation of the available data is that it does not report the commuting zone of residence but only the more aggregated department of residence as our sample contains 93 departments. Using information on the department of residence, we can however check whether those job transitions across commuting zones are associated with an actual change of department of residence.

We start in Appendix Panel B of Table A14 by studying the extent to which job mobility across commuting zones related to immigration is simultaneously associated with in changes the department of residency. We compare our baseline results reported in panel A (reproduced for convenience from Panel 2 of Table 4), where our dependent variable is the probability to change commuting zone for the job, with result in panel B where the dependent variable is the probability of changing at the same time the commuting zone for the job and the department of residency. Compared to the results including all transitions, transitions with change of department of residence display the same signs except for managers (where the coefficient remains anyway statistically insignificant) and are significant for the same groups of workers. Quantitatively, a comparison between the estimates in panels A and B indicates that between a third and half of the transitions linked to immigration result in a change of department of residence.

In Table A15, we investigate whether change of department of residence is associated to a differential adjustment of daily wages for blue-collar workers, again comparing with the baseline results (Columns 1 and 4 reproduce the results of Panel D Table 7, and columns 2 and 5 those for Panel A in Table 10). Clearly, the results in columns 3 and 6 suggest that most of the additional negative effects of immigration on the wages of movers correspond to workers changing their department of residence.

A8. Estimates by Decades

In Table A16, we explore how our results vary across periods. For 1975-1982, the signs and coefficients are broadly similar to those for the overall period but the standard errors are much larger. From 1990, although the standard errors are sometimes substantially larger than in the pooled estimates, the results appear also reasonably consistent for most outcomes, and particularly so for the probability to leave the commuting zone and the impact on wages. The first-difference 1982-1990 is an exception as little significant impact is found and the coefficients are often different, which might be due to the past settlement instrument being problematic during that period. Indeed, as shown in Table 1, and in contrast to other periods, the correlation between the predicted inflow rates and their lagged values is above 0.9 in 1982-1990. As inflows tend to overlap in this decade, the short and medium run adjustment to immigration are hard to separate (Jaeger, Ruist, et Stuhler 2018).

A9. Controlling for industry-specific trends

One important concern is that the location choice of immigrants might be persistently correlated with the local composition of industries. More precisely, our estimates might be biased if the initial distribution of immigrants in 1975 is correlated with persistent differences in industry composition across commuting zones that also drive the evolution of wages.

To directly control for the effect of the local specialization of industries on wages, we propose an alternative residualizing of wages using industry dummies for 40 industries interacted with year dummies (see below for the NAP 40 definition) in addition to age dummies. As wages are residualized using a separate regression for each census year, this procedure accounts for the effects on wages of every national-level industry-specific trend. The coefficients for the regression on wages based on this alternative residualization are presented in Appendix Table A17. Even if the point estimates become more imprecise, the coefficients tend to be quite similar to the benchmark in Table 7.

Local initial differences in industry composition might also affect labor demand across commuting zones. Following Jaeger, Ruist, et Stuhler (2018), a direct method to control for the effect of differences in local industry composition on local labor demand is to construct a standard Bartik instrument predicting local demand shocks and controlling for this effect in the regression. For each commuting zone l and census year t, the Bartik instruments are given by

$$\Delta D_{lt} = \sum_{s} \phi_{sl,95}(emp_{st}^{ref} - emp_{s,t-1}^{ref})$$

where $\phi_{sl,75} = \frac{Emp_{sl,75}}{Emp_{l,75}}$ is the initial share of workers in industry s in commuting zone l in 1975, and $(emp_{st}^{ref} - emp_{s,t-4}^{ref})$ is the change in *national* level log employment in industry s between two censuses. As expected, the results reported in panel B of Appendix Table A17 show the local Bartik shocks to be positively correlated with wage changes in the commuting zone for most groups except surprisingly for blue-collar workers. However, controlling for the Bartik shocks does not change substantially the coefficient of the estimated impact of immigration on wages.

Another possibility is that the effects of immigration vary with the initial industry composition of commuting zones or their size in terms of total population. Gould (2019)[53], shows that low-skill immigration in the US has a larger negative effect on the wages of unskilled workers in regions hardly hit by the decline in manufacturing employment.

We report in Appendix Table A18 estimates of models that include an interaction term between the immigrant ratio and a dummy for each quartile of distribution of the initial share of employment in 1976 in the tradable sector, the non-tradable sector, and the construction sector, in Columns 2, 3 and 4 respectively. If anything, the results suggest that immigration might have lower effects on wages in commuting zones that had initially a larger share of workers in the tradable industry than in the non-tradable industry. In Column 5, we test whether the effect of immigration varies with the initial size of the population in the commuting zone. Even if the coefficients are also imprecise, the results suggest that the impact of immigration on wages might be twice as low in larger commuting zones than in the top quartile of the population distribution.

Crosswalk tables for industry classifications: We use the industry classification that 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

[53] Gould, Eric D. 2019. "Explaining the Unexplained: Residual Wage Inequality, Manufacturing Decline and Low-Skilled Immigration." The Economic Journal 129 (619): 1281–1326.

panel 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 panel from 1993 to 2002. For the match between NAP and NAF, we have used the 1994 Labor Force Survey (*Enquête emploi*) in which both codes are available to establish a match at the four-digit level using the most frequent correspondence when several possibilities existed. The match has been completed manually to include exhaustively all codes in the four-digit level correspondence table.

Supplementary Appendix Tables

Table A1: Annualized share of new immigrants as a percentage of the country's population for France and the US

France		U.S.	
Period	Share	Period	Share
1968-75	0.28	1970-80	0.25
1975-82	0.18		
1982-90	0.15	1980-90	0.36
1990-99	0.13	1990-99	0.43
1999-2007	0.25	1999-2010	0.32

Source: For France, 1968, 1975, 1982, 1990, 1999 and 2007 Censuses, calculations from the authors. For the US, Jaeger *et al.* (2018) from the 1970, 1980, 1990, 1999 and 2010 Censuses. Note: The table shows the (compound) annual percentage share of recent immigrants in the population. For both France and the US, recent immigrants are defined as immigrants who were not present in the previous census.

Table A2: Percentage share of foreign-born workers within occupation along the wage distribution in 2007

Rank in wage distribution	**All**	**P10**	**Q1**	**Q2**	**Q3**	**Q4**	**P90**
Managers	11.3	14.1	11.6	9.5	10.4	13.6	15.3
Technicians and clerks	8.4	11.4	9.8	7.8	7.5	8.5	9.2
Skilled blue-collar	13.4	21.8	17.4	11.3	11.5	13.5	14.8
Unskilled blue-collar	18.4	21.3	21.1	18.9	15.7	18.1	20.1

Source: DADS panel, 2007. Note: The table documents the percentage share of foreign-born workers in percentage point by occupations groups across different part of the age-adjusted wage distribution: first decile (P10), first quartile (Q1), second quartile (Q2), third quartile (Q3), ninth-decile (P90).

Table A3: Attrition in sample by periods and occupations

Period in Census	1975-1982	1982-1990	1990-1999	1999-2007	1975-2007
Corresponding Period in DADS	1976-1982	1982-1991	1991 -1999	1999-2007	1976-2007
	A. Age brackets by first-differences				
Age in first-period	25-50	25-50	25-50	25-50	25-50
Age in second-period	31-56	34-59	33-58	33-58	n.a.
	B. Selection in the balanced samples by period				
Initial number of workers in first-period, age 25-50	188,765	196,457	252,827	252,164	880,213
Share unobserved in second-period	23.1	25.7	21.7	19.4	22.2
Number of workers in the 3-year sample	214,407	238,424	272,521	274,247	999,500
Share of unobserved in first-period for the 3-year sample	15.5	21.5	21.7	15.9	18.7
Number of workers in the 5-year sample	220,596	244,542	281,448	288,751	1,035,337
Share of unobserved in first-period for the 5-year sample	10.4	18.9	19.8	12.4	16.4
	C. Selection in balanced samples by occupation				
Initial occupation	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars	All
Initial number of workers observed in first-period	128,637	181,543	398,051	171,982	880,213
Share unobserved in period second-period	21.3	19.6	21.6	27.3	22.2

Source: DADS panel. Notes: Panel A documents differences in the age brackets in the second period of each first-differences. Panel B and C show how many workers are observed in the sample in the first-period but not observed in the second period for each first-differences in Panel B and occupation groups in Panel C. 3- and 5-year samples refer to samples using respectively 3 and 5 years windows to measure outcomes.

Table A4: Do Immigrant Inflows Influence Attrition?

Dependent variable: *Probability of not being observed in the sample in t* Sample: Male workers 25-50 in first-period.					
	(1)	(2)	(3)	(4)	(5)
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
	A. Aggregate 2SLS Estimates with instrument base period 1975				
Immigrant inflow	0.034	-0.474	0.035	0.288	-0.346
	(0.156)	(0.292)	(0.220)	(0.196)	(0.263)
N	1144	1144	1144	1144	1144
First Stage F-stat	38.4	38.4	38.4	38.4	38.4
	B. 2SLS Estimates with instrument base period 1975				
Immigrant inflow	0.127	-0.323	0.095	0.294*	-0.285
	(0.143)	(0.289)	(0.216)	(0.176)	(0.235)
Full year worker	-0.172***	-0.171***	-0.180***	-0.156***	-0.175***
	(0.002)	(0.010)	(0.008)	(0.004)	(0.005)
Log daily wage	-0.088***	-0.064***	-0.088***	-0.113***	-0.097***
	(0.002)	(0.005)	(0.004)	(0.003)	(0.004)
Age	-0.032***	-0.027***	-0.028***	-0.044***	-0.024***
	(0.001)	(0.005)	(0.003)	(0.002)	(0.003)
$Age^2/100$	0.051***	0.039***	0.043***	0.066***	0.042***
	(0.002)	(0.007)	(0.005)	(0.003)	(0.004)
N	880,558	181,543	398,051	171,982	128,982
First Stage F-stat	34.2	18.7	33.0	30.1	62.0

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes:. The dependent variable is the probability of not being observed in the sample in Census year *t* conditional on having been observed in the sample in Census year *t-1*. The instrument for changes in the immigration ratio is the past settlement instrument base period 1975. All regressions include a full set of region and time fixed-effects and their interaction with the start-of-period share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using inflows into 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A5: Long Run Wage Responses to Immigration

	Dependent variable: *Average change in log residual daily wages between t-2 and t* Sample: Male workers 25-50 in first period				
	All	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
	2SLS estimates using baseline location				
Recent inflows	-0.453	-0.891	-0.571	-0.405	-1.393*
	(0.313)	(1.309)	(0.463)	(0.336)	(0.763)
Distant inflows	-0.008	1.849*	0.100	0.123	0.270
	(0.234)	(0.989)	(0.388)	(0.333)	(0.599)
N	858	858	858	858	858
First Stage F-stat	10.4	10.4	10.4	10.4	10.4

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All panels show regression results at the commuting zone level where the dependent variable is the average change in residual log daily wages. The residual wages have been obtained in an individual-level regression on age dummies estimated separately on each census year and occupation group. Each column reports estimates of the model on a different group of workers defined by their initial occupation and commuting zone. The model is estimated on a balanced panel including all individuals initially in the occupation/location independently on their final destination in period *t.* The models are estimated with 2SLS using the recent and distant settlement instrument base period 1975 for the recent and distant change in the immigrant inflow. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, and with the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Locations are defined using the initial location across 286 commuting zones and changes in immigration ratio are measured over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A6: Effects of Immigration on Wages for Natives in the Lowest Wage Quartiles, 2SLS

Dependent variable: *change in log residual daily wages between t-1 and t* Sample: Male workers 25-50 in first-period			
	(1)	(2)	(3)
	A. Individuals with residual wage in the lowest wage quartile in *t-1*		
Immigrant inflow	-0.414	0.147	1.153
	(0.306)	(0.317)	(0.719)
Immigrant inflow x Unskilled Blue Collar in t-1		-1.681***	-2.671***
		(0.541)	(0.793)
Immigrant inflow x Skilled Blue Collar in t-1			-1.657*
			(0.900)
N	168,970	168,970	168,970
	B. Individuals with residual wage in the second quartile in *t-1*		
Immigrant inflow	0.037	0.142	0.896
	(0.199)	(0.204)	(0.611)
Immigrant inflow x Unskilled Blue Collar in t-1		-0.502	-1.262**
		(0.402)	(0.465)
Immigrant inflow x Skilled Blue Collar in t-1			-1.181***
			(0.284)
N	168,413	168,413	168,413
F-stat	37.8	19.2	12.6

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: all panels show regression results at the individual level where the dependent variable is the change of residual log daily wages. The residual wages have been obtained with individual-level regressions on age dummies estimated separately on each census year and occupation group. Panels A and B present regressions for natives belonging in the first period to respectively the first and the second wage quartile. The models are estimated on a balanced panel with 2SLS using the past settlement instrument base period 1975 for the change in the immigration ratio and its interaction with a dummy variable indicating whether the workers was initially unskilled blue-collar and skilled blue-collar. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, and with the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using the initial location and occupation across 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. All regressions are weighted using the inverse of the number of observations per commuting zone. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A7: Imputation on those unobserved in second period

Sample group under consideration among male workers 25-50 in first-period					
A. Stayers imputed on those unobserved in second period					
	Dependent variable: *Adjusted probability to leave the commuting zone between two consecutive Census years*				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
Immigrant inflow	0.462	0.090	0.301	1.201***	0.616
	(0.298)	(0.579)	(0.484)	(0.359)	(0.389)
Rank wage(t-1) x Immigrant inflow	0.445	1.791***	0.822	-0.975**	-0.161
	(0.258)	(0.691)	(0.582)	(0.471)	(0.538)
Rank wage(t-1)	0.035***	0.075***	0.039***	-0.066***	-0.080***
	(0.004)	(0.013)	(0.008)	(0.005)	(0.007)
B. Movers imputed on those unobserved in second period					
	Dependent variable: *Adjusted probability to leave the commuting zone between two consecutive Census years*				
Immigrant inflow	0.728*	-0.075	0.889*	1.436***	1.497**
	(0.325)	(0.852)	(0.490)	(0.492)	(0.605)
Rank wage(t-1) x Immigrant inflow	-0.145	0.914	-0.126	-1.718**	-1.822**
	(0.312)	(1.082)	(0.609)	(0.635)	(0.960)
Rank wage(t-1)	-0.096***	-0.008	-0.064***	-0.172***	-0.221***
	(0.005)	(0.014)	(0.008)	(0.006)	(0.008)
N	849,570	108,934	297,369	313,496	129,771
First Stage F-stat	12.4	12.6	12.5	12.4	12.4

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show estimates of regressions where the dependent variable is the age-adjusted probability for a native worker to work by census *t* in a different commuting zone than in census *t-1*. Each column reports estimates of the model on a different group of workers defined by their initial occupation and commuting zone in period *t-1*. The sample includes workers unobserved in the second period by imputing as outcome in Panel A (resp. in Panel B) that they stayed (resp. left) the location or occupation. Regressions are weighted using the inverse of the number of observations per commuting zone. The instruments are the past settlement base period 1975 and its interaction with the initial wage rank. The models include a full set of region and time fixed-effects and their interaction with the start-of-period log number of employees, and with the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using mobility across 286 commuting zones and changes in immigration ratio in the origin commuting zone over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A8: Controlling for Baseline Rates

Sample group under consideration among male workers 25-50 in first-period					
	A. Dependent variable: *Adjusted probability to leave the commuting zone between two consecutive Census years*				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
Immigrant inflow	0.635**	0.273	0.786	1.470***	0.416
	(0.322)	(1.040)	(0.530)	(0.432)	(0.484)
Rank wage(t-1) x Immigrant inflow	-0.134	1.520	-0.034	-1.381***	-0.104
	(0.402)	(1.546)	(0.710)	(0.465)	(0.725)
Rank wage(t-1)	0.029***	0.054***	0.044***	-0.104***	-0.147***
	(0.006)	(0.023)	(0.013)	(0.008)	(0.012)
Lagged baseline outflow rate	0.505***	0.076*	0.330***	0.360***	0.265***
of the group in the CZ	(0.052)	(0.043)	(0.053)	(0.056)	(0.052)
N	677,740	87,381	241,203	253,891	95,265
First Stage F-stat	7.9	8.3	8.2	8.3	8.3
	B. Dependent variable: *inflows into the group in the commuting zone between two consecutive censuses*				
Immigrant inflow	0.020	0.585	0.352	-0.208	-0.554
	(0.209)	(0.623)	(0.371)	(0.283)	(0.581)
Lagged baseline inflow rate	0.275***	0.381***	0.378***	0.381***	0.537***
of the group in the CZ	(0.057)	(0.049)	(0.054)	(0.051)	(0.080)
N	1144	1144	1144	1144	1144
First Stage F-stat	24.7	24.7	23.3	25.8	24.6

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show estimates of regressions where the dependent variable is the age-adjusted probability for a native worker to leave the commuting zone in Panel A, or the inflow rate to the commuting zone in Panel B. Each column reports estimates of the model on a different group of workers defined by their initial occupation and commuting zone in period *t-1*. Regressions are weighted using the inverse of the number of observations per commuting zone. The instruments are the past settlement base period 1975 and its interaction with the initial wage rank. All regressions control for the initial baseline mobility rates. The models include a full set of region and time fixed-effects and their interaction with the start-of-period log number of employees, and with the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using mobility across 286 commuting zones and changes in immigration ratio in the origin commuting zone over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A9: Effects of Immigration on Wages by Initial Industry

	Dependent variable: *change in log residual daily wages between t-1 and t* Sample: Male workers 25-50 in first-period			
	Skilled blue-collar workers in *t-1*		Unskilled blue-collar workers in t-1	
Immigrant inflow	-0.334***	0.365	-0.987**	0.117
	(0.128)	(0.307)	(0.482)	(0.542)
Immigrant inflow x Non-Tradable Sector in *t-1*		-1.072***		-2.047***
		(0.272)		(0.520)
Immigrant inflow x Construction in *t-1*		-0.217		-1.840**
		(0.223)		(0.782)
N	253,891	253,891	95,265	95,265
F-stat	37.8	12.2	37.8	12.1

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show regression results at the commuting zone level where the dependent variable is the change in residual log daily wages. Each column reports estimates of the model on a different group of workers defined by their initial occupation and commuting zone. The models are estimated with 2SLS using the past settlement instrument base period 1975 instrument for the change in the immigration ratio. All regressions include a full set of time fixed effects and their interaction with the start of period share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in immigration ratio over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5% level, and 1% level.

Table A10: Do the Effects of Immigration Differ by Age?

	Sample group under consideration among male workers 25-50 in first-period				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
	2SLS Estimates with instrument base period 1975				
	A. Dependent variable: *Adjusted probability to leave the commuting zone*				
Immigrant inflow	0.869**	1.499	1.231***	0.854**	0.658
	(0.355)	(0.972)	(0.461)	(0.371)	(0.467)
Immigrant inflow x Age 35-44 in *t-1*	-0.085	-0.687	-0.650*	0.032	0.324
	(0.191)	(0.712)	(0.357)	(0.197)	(0.443)
Immigrant inflow x Age 45-50 in *t-1*	-0.314	-1.536*	-0.744*	-0.248	-0.671
	(0.223)	(0.835)	(0.418)	(0.219)	(0.551)
N	677,740	87,381	241,203	253,891	95,265
First Stage F-stat	8.3	8.3	8.3	8.3	8.3
	B. Dependent variable*: Change in average log residual daily wages*				
Immigrant inflow	-0.248	-0.898	-0.589**	-0.481***	-1.247**
	(0.171)	(0.625)	(0.291)	(0.178)	(0.496)
Immigrant inflow x Age 35-44 in *t-1*	0.111	0.707	0.602	0.376	1.156***
	(0.256)	(0.701)	(0.413)	(0.282)	(0.442)
Immigrant inflow x Age 45-50 in *t-1*	-0.170	1.831	-0.189	0.184	-0.427
	(0.272)	(1.286)	(0.388)	(0.366)	(0.620)
	C. Dependent variable*: Change in average residual log annual days worked*				
Immigrant inflow	-0.172	-0.962**	-0.359*	-0.059	-0.153
	(0.145)	(0.410)	(0.209)	(0.153)	(0.353)
Immigrant inflow x Age 35-44 in *t-1*	0.237	0.241	0.132	0.502**	1.069***
	(0.200)	(0.443)	(0.358)	(0.197)	(0.497)
Immigrant inflow x Age 45-50 in *t-1*	0.457*	0.928	1.015**	0.144	-0.245
	(0.234)	(0.879)	(0.420)	(0.287)	(0.775)
N	677,740	87,381	241,203	253,891	95,265
F-stat	12.5	12.5	12.5	12.5	12.5

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All panels show regression results at the commuting zone level where the dependent variable is the adjusted probability to leave the commuting zone in Panel A, the change in residual log daily wages in Panel B, the change in average residual log annual days worked Panel C. Each column reports estimates of the model on a different group of workers defined by their initial occupation and commuting zone. The model contains specific interaction terms between immigrant inflows and the initial age group of the worker in the first period of each first-difference. All models are estimated with 2SLS using the past settlement instrument base period 1975 instrument for the change in the immigration ratio and its interaction with the age group definitions. All regressions include a full set of time fixed effects and their interaction with the start of period share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in immigration ratio over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5% level, and 1% level.

Table A11: Impact of Immigration on Native Outflows from departments, 1975-2007

Dependent variable: *Adjusted probability to leave the department between two consecutive Census years*					
	Sample group under consideration among male workers 25-50 in first-period				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
	A. OLS Estimates				
Immigrant inflow	-0.098	-0.276	-0.080	-0.142	-0.016
	(0.168)	(0.257)	(0.171)	(0.189)	(0.152)
	B. 2SLS Estimates with instrument base period 1975				
Immigrant inflow	0.482	0.053	0.456	1.108*	1.369*
	(0.481)	(0.638)	(0.496)	(0.610)	(0.700)
N	372	372	372	372	372
First Stage F-stat	18.4	18.4	18.4	18.4	18.4
	C. 2SLS Estimates allowing for selection				
Immigrant inflow	0.523	-1.480	0.288	2.453**	1.825*
	(0.845)	(0.900)	(0.810)	(0.579)	(1.014)
Rank wage(t-1) x Immigrant inflow	-0.613	0.738	-0.603	-2.223***	-0.613
	(0.437)	(0.866)	(0.370)	(0.353)	(0.508)
Rank wage(t-1)	0.052***	0.050***	0.046***	-0.046***	-0.090***
	(0.005)	(0.012)	(0.006)	(0.005)	(0.007)
N	677,740	87,381	241,203	253,891	95,265
First Stage F-stat	13.2	14.4	13.5	12.9	11.8
Baseline rate	10.9	17.6	12.8	7.9	8.1
Share in group	100%	13%	36%	37%	14%

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show estimates of regressions where the dependent variable is the age-adjusted probability for a native worker to leave by census *t* the department observed in census *t-1*. Each column reports estimates of the model on a different group of workers defined by their initial occupation and department in *t-1*. Panel A and B show regressions using department averages, whereas Panel C shows regressions at the individual level. Each column reports estimates of the model on a different group of workers defined by their initial occupation and department in period t-1. The models are estimated with OLS in panel A and with 2SLS in Panels B and C. Regressions in panel C are weighted using the inverse of the number of observations per department. The instruments are the past settlement base period 1975 and its interaction with the initial wage rank in panel C. All regressions include a full set of region and time fixed-effects and their interaction with the start-of-period log number of employees, and the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using observed job mobility across 93 department*s* and changes in the immigration ratio in the origin 93 departments over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A12: Impact of Immigration on Native Inflows into departments, 1975-2007

Dependent variable: *inflows into the group in the department between two consecutive censuses* Sample: Male workers 25-50 in first-period.					
	(1)	(2)	(3)	(4)	(5)
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
	A. OLS Estimates				
Immigrant inflow	0.378***	0.636***	0.317***	0.306***	0.222**
	(0.070)	(0.148)	(0.105)	(0.118)	(0.106)
N	372	372	372	372	372
	B. 2SLS Estimates with instrument base period 1975				
Immigrant inflow	0.151	0.628	0.178	-0.309	-0.285
	(0.220)	(0.398)	(0.219)	(0.299)	(0.271)
N	372	372	372	372	372
First Stage F-stat	25.3	25.3	25.3	25.3	25.3
	C. 2SLS Estimates allowing for selection				
Immigrant inflow	0.083	0.262	0.151	-0.290	-0.327
	(0.237)	(0.402)	(0.244)	(0.228)	(0.257)
Rank wage(t-1) x Immigrant inflow	0.075	0.316	-0.042	-0.136*	0.166
	(0.052)	(0.250)	(0.045)	(0.081)	(0.144)
Rank wage(t-1)	-0.000	-0.005	0.001	-0.003	-0.001
	(0.000)	(0.004)	(0.001)	(0.001)	(0.002)
N	677,740	87,381	241,203	253,891	95,265
First Stage F-stat	13.2	14.4	13.5	12.9	11.8
Baseline rate	10.9	17.6	12.8	7.9	8.1
Share in group	100%	13%	36%	37%	14%

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: The panels show regression results at the department level where the dependent variable is the share of natives joining the department within each specified occupation between census *t-1* and *t*. The models are estimated with OLS in Panel A and 2SLS in Panel B. The instrument for changes in immigration ratio in Panel B is the past settlement instrument base period 1975. All regressions include a full set of region and time fixed effects and their interaction with the start-of-period share of employment in the department in the tradable, non-tradable and construction sectors. Regressions are estimated using 93 departments and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A13: Impact of Immigration on Log Daily Wages, department level estimates

	Sample group under consideration among male workers, 25-50 in first-period.				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
Dependent variable*: Change in average log residual daily wages between two censuses in the commuting zone*					
	A. OLS Estimates using current location				
Immigrant inflow	0.295***	0.188	0.309*	0.073	0.157
	(0.102)	(0.163)	(0.163)	(0.079)	(0.169)
	B. 2SLS Estimates using current location				
Immigrant inflow	0.301	-0.290	-0.208	-0.043	0.527
	(0.201)	(0.449)	(0.308)	(0.150)	(0.342)
	C. OLS Estimates using baseline location				
Immigrant inflow	0.084	0.051	-0.009	0.055	0.040
	(0.056)	(0.126)	(0.081)	(0.058)	(0.085)
	D. 2SLS Estimates using baseline location				
Immigrant inflow	-0.081	-0.103	-0.224	-0.265**	-0.220
	(0.132)	(0.354)	(0.191)	(0.123)	(0.219)
N	372	372	372	372	372
First Stage F-stat	25.3	25.3	25.3	25.3	25.3

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census. Notes: The dependent variable in Panels A and B is the change in average log residual daily wages in the department. Panel C show results from a balanced sample where the dependent variable is the average change in log residual daily wages for individuals initially in a given occupation by location cell. The sample in Panel C includes all workers initially observed in the occupation x department cell. The models are estimated with OLS in Panel A and with 2SLS in the other panels using the past settlement instrument base period 1975. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the department in the tradable, non-tradable and construction sectors. Regressions are estimated using 93 departments and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A14: Effects of immigration on job and residential mobility across departments

	Sample group of movers under consideration among male workers 25-50 in first-period				
	All employees	Managers	Technicians and clerks	Skilled blue-collars	Unskilled blue-collars
	A. Dependent variable: *Adjusted probability to leave the commuting zone*				
Immigrant inflow	0.790**	0.810	0.903**	0.818**	0.652
	(0.332)	(0.709)	(0.410)	(0.340)	(0.426)
	B. Dependent variable: *Adjusted probability to leave the commuting zone and change department of residence*				
Immigrant inflow	0.222*	-0.523	0.424*	0.232**	0.325
	(0.121)	(0.474)	(0.230)	(0.098)	(0.207)
N	1144	1144	1144	1144	1144
First Stage F-stat	24.2	24.2	24.2	24.2	24.2

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: In Panel A, the dependent variable is the age-adjusted probability for a native worker to work by census *t* in a commuting zone different to that in census *t-1*. In panel B, the dependent variable is the probability to work in a different commuting zone and to be observed as being resident in a different French department. Each column reports estimates of the model on a different group of workers defined by their initial occupation and commuting zone in *t-1*. The models are estimated with 2SLS. The instruments are the past settlement base period 1975. All regressions include a full set of region and time fixed-effects and their interaction with the start-of-period log number of employees, and the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in the immigration ratio in the origin commuting zone over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A15: Effects of job and residential mobility on wages

Dependent variable: *Change in log residual daily wages between t-1 and t*						
	Skilled blue collar			Unskilled blue collar		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant inflow	-0.334***	-0.239*	-0.240*	-0.987**	-0.719*	-0.720*
	(0.128)	(0.132)	(0.132)	(0.482)	(0.390)	(0.392)
Immigrant Inflow x job location shifter dummy		-0.320			-1.150*	
		(0.272)			(0.664)	
Job location shifter dummy		-0.007*			0.037***	
		(0.004)			(0.008)	
Immigrant Inflow x job location shifter and change department of residency dummy			-0.893*			-1.304**
			(0.458)			(0.621)
Immigrant Inflow x job location shifter and same department of residency dummy			-0.011			-1.046
			(0.421)			(1.080)
Job location shifter and change department of residency dummy			0.012*			0.065***
			(0.007)			(0.014)
Job location shifter and same department of residency dummy			-0.017***			0.023**
			(0.005)			(0.011)
N	253,891	253,891	253,891	95,265	95,265	95,265
First Stage F-stat	38.4	18.7	12.3	38.4	18.7	12.5
Period	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007	1975-2007

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All columns show individual level regression results where the dependent variable is the change in residual log daily wages between census year *t-1* and year *t* for natives in the indicated occupation group in *t-1*. The models in column 2 and 5 include an interaction term between immigration and change in commuting zone of the job of the workers. The models in columns 3 and 5 include an additional interaction term between changing commuting zone for the job and changing the department of residency. All regressions are weighted using the inverse of the number of workers initially in each commuting zone. The residual wages have been obtained in an individual-level regression on age dummies estimated separately on each census year and occupation group. The models are estimated with 2SLS using the past settlement instrument base period 1975 for the change in the immigration ratio. We also use as instruments the interaction between the past settlement instrument with the location shifter dummies when the model includes interaction terms. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Locations are defined using the initial location across 286 commuting zones and changes in immigration ratio are measured over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A16: 2SLS Estimates by Decade

Sample: Male skilled blue-collar workers 25-50 in first-period.

	(1)	(2)	(3)	(4)	(5)
	Overall period	1975-82	1982-90	1990-99	1999-2007
	A. Dependent variable: *Adjusted probability to leave the commuting zone*				
Immigrant inflow	1.638***	0.879	0.677	2.456***	2.960***
	(0.450)	(0.760)	(0.501)	(0.665)	(1.005)
Rank wage(t-1)	-1.618***	-2.240**	-0.129	-0.778	-0.469
x Immigrant Inflow	(0.523)	(1.030)	(0.673)	(0.582)	(0.763)
Rank wage(t-1)	-0.091***	-0.064***	-0.072**	-0.122**	-0.136**
	(0.006)	(0.014)	(0.011)	(0.013)	(0.014)
N	253,891	54,388	52,172	71,038	76,291
First Stage F-stat	12.4	15.1	22.4	10.7	10.8
	B. Dependent variable: *Inflows into the skilled blue-collar occupations*				
Immigrant inflow	-0.463**	-0.436	0.298	-1.475**	-0.905**
	(0.211)	(0.488)	(0.238)	(0.648)	(0.428)
	C. Dependent variable: *Average change in log residual daily wages*				
Immigrant inflow	-0.334***	-0.427	0.298	-0.976**	-0.905*
	(0.128)	(0.307)	(0.170)	(0.448)	(0.428)
N	1144	286	286	286	286
First Stage F-stat	38.4	47.0	21.5	14.9	11.6

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All regressions are conducted on a balanced panel of male natives who are in skilled blue-collar jobs in census *t-1*. Column 1 reproduces the baseline results for the overall period, whereas Columns 2 to 5 present the results for specific decades. The dependent variable in each panel has been adjusted for differences in age using the residuals from a regression of the probability to change occupations on age dummies estimated separately on each census year. Panels A show regression results at the individual level where the dependent variables are the adjusted probabilities of leaving the commuting zone between census *t-1* and census *t*. Panel B shows regression results at the commuting zone level where the dependent variable is the inflow rate into the skilled blue-collar group in the commuting zone in between census *t-1* and census *t*. Panel C shows regression results at the commuting zone level where the dependent variable is the average change in residual log daily wages. The instrument for changes in the immigration ratio is the past settlement instrument base period *t-2* in all panels. Regressions are estimated using the initial location across 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A17: Controlling for industry trends and local industry shocks

Sample: male workers 25-50 in first-period.					
	All employees	Managers	Technicians and clerks	Blue-collars	
				Skilled	Unskilled
	Dependent variable: *average change in log residual daily wages between t-1 and t, Balanced 2SLS Estimates*				
	A. Wages residualized with industry x year fixed effects				
Immigrant inflow	-0215*	-0.315	-0.305	-0.186	-0.865**
	(0.118)	(0.535)	(0.199)	(0.134)	(0.390)
N	1144	1144	1144	1144	1144
First-Stage	36.3	36.3	36.3	36.3	36.3
	B. Controlling for Bartik Employment shocks, 2-digit industry level				
Immigrant inflow	-0.267***	-0.259	-0.472**	-0.348***	-1.032**
	(0.124)	(0.558)	(0.223)	(0.131)	(0.497)
Bartik industry	0.097**	0.427**	0.176**	0.048	0.150
shock	(0.050)	(0.171)	(0.086)	(0.047)	(0.119)
N	1144	1144	1144	1144	1144
First-Stage	37.4	37.4	37.4	37.4	37.4

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: Panel A and B show regression results where the dependent variable is the change in average log residual daily wages per worker in the commuting zone. Panel A shows regressions in which wages have been residualized using 40 industry fixed effects interacted with time in addition to age dummies. In panel B, the model controls for Bartik shocks to local employment based on the initial distribution of industries in 1975. The models are estimated with 2SLS using the past settlement instrument base period 1975 for the change in the immigration ratio. All regressions include a full set of time fixed effects and their interaction with the start-of-period log number of employees, and the share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using either the actual or initial location and occupation across 286 commuting zones and changes in immigration ratios over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5%, and 1% level.

Table A18: Effect of Immigration on Wages by Industry Composition or Population of the Commuting Zone in 1976, 2SLS

Dependent variable: Average change in log residual daily wages between t-1 and t Sample: Male unskilled blue-collar workers 25-50 in first-period.					
	Benchmark	Commuting zones distribution in 1976 in terms of:			
		Share of tradable industries	Share of non-tradable industries	Share of Construction Sector	Population Size
	(1)	(2)	(3)	(4)	(5)
Immigrant inflow	-0.987**	-1.780**	0.154	-0.873	-2.645*
	(0.482)	(0.838)	(0.728)	(0.836)	(1.564)
Immigrant inflow x Q2 distribution		0.951	-0.621	-0.044	1.073
		(0.831)	(0.790)	(0.843)	(1.620)
Immigrant inflow x Q3 distribution		1.293	-2.220*	0.173	1.961
		(0.912)	(1.255)	(0.879)	(1.533)
Immigrant inflow x Q4 distribution		1.788*	-1.179	-0.457	2.448
		(1.079)	(0.847)	(1.033)	(1.587)
N	1144	1144	1144	1144	1144
F-stat	38.4	2.4	2.3	2.6	4.3

Sources: Data are from the DADS panel 1976-2007 except for the immigration inflow and the instrument, coming from Census data. Notes: All panels show regression results at the commuting zone level where the dependent variable is the average change in residual log daily wages. Column 1 reproduces the benchmark result from Panel C of Table 7, whereas Columns 2 to 5 consider in turn how the endogenous variable changes depending on the position of the location along the distribution of commuting zones based on the variable specified in the column. The models are estimated with 2SLS using the past settlement instrument base period 1975 for the change in the immigration ratio and in Columns 2 to 5 also its interaction with the dummies indicating if the commuting zone belonged to the second, third or fourth quartile of the distribution for the relevant variable. All regressions include a full set of time fixed effects and their interaction with the start of period share of employment in the commuting zone in the tradable, non-tradable and construction sectors. Regressions are estimated using 286 commuting zones and changes in the immigration ratio over 1975-82, 1982-90, 1990-99, 1999-2007. Standard errors are clustered at the commuting zone level. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5% level, and 1% level.

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