Moving up or down? Immigration and the selection of blue-collar natives across occupations and locations*

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15 March 2017

Abstract

Exploiting a large French panel for 1976-2007, we examine how immigration affects the selection of blue-collar natives across local labour markets. Immigration inflows generate substantial reallocations of blue-collar natives across locations, industries and occupations. Location movers are negatively selected while occupation movers are positively selected and move towards better-paid jobs with less routine tasks. As a result, controlling for composition effects has an important impact on the estimates of the wage impact of immigration. Overall, immigration moderately lowers the wages of blue-collar workers. Workers changing location experience the largest wage losses while those changing occupation are less affected.

JEL: J15, J31.

Keywords: Immigration, Wages, Employment.

* A previous version of this paper circulated under the title "The impact of immigration on the local labor market outcomes of blue-collar workers: panel data evidence". We thank the INSEE for making the data available. The Census data used in this paper are available upon request for researchers from the Centre Maurice Halbwachs. The authors accessed the DADS data via the *Centre d'Accès Sécurisé Distant* (CASD), dedicated to the use of authorized researchers, following the approval of the *Comité français du secret statistique*. The views expressed here do not necessarily reflect those of any of the organizations with which the authors are affiliated. We also thank Denis Fougère, Kyle Mangum, Manon Dos Santos, Muriel Roger, Ahmed Tritah and seminar participants at AMSE, Norface, SOLE, IZA-SOLE, CEP (LSE), and ESSLE-CEPR for very useful suggestions. This research was supported by a French state grant (grant no. ANR-10-EQPX-17) (Centre d'accès sécurisé aux données (CASD)), the LABEX OSE of the Paris School of Economics (ANR-10-LABX_93-01), the CEPREMAP's *Programme Travail* and the "Flash Asile" programme of the French *Agence Nationale de la Recherche* (ANR-16-FASI-0001).

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Introduction

While much progress has been made, the assessment of how immigration changes natives' labour market outcomes still faces many empirical challenges. Under competitive labour markets, an increase in labour supply induced by immigration should lower the wages of competing workers. However, how to identify of the groups of natives directly competing with immigrants remains controversial.

A recent strand of the literature proposed to use education and experience to define the groups of immigrants and natives in competition (see e.g. Borjas, 2003, or Aydemir and Borjas, 2007). However, immigrants may be quite different from natives with a similar educational level because of their lack of language fluency or the lower value of foreign education in the host country (Friedberg, 2000). Several recent studies indicate that immigrants "downgrade" at arrival in the sense that they work in jobs of much lower quality than similar natives (Cohen-Goldner and Paserman, 2011; Dustmann and Preston, 2012). As a result, immigrants and natives with the same education and experience might not really compete for the same jobs (Dustmann, Frattini and Preston, 2013) and might be imperfect substitutes (Ottaviano and Peri, 2012).[4]

In this paper, we exploit panel data to study the labour market outcomes of blue-collar natives across locations that were differently exposed to immigration inflows over time. However, instead of making assumptions about which observable individual characteristics make natives and immigrants similar, we study whether the impact of immigration varies across subgroups of blue-collar employees depending on their initial industry/occupation. Indeed, blue-collar natives in specific industries/occupations may be more exposed to

[4]See also Manacorda, Manning, and Wadsworth (2012) for evidence that immigrants and natives might be imperfect substitutes within education/experience cells in the UK. Peri and Sparber (2009) shows that low-skill natives in local labour markets receiving more immigrant inflows tend to specialize in occupations requiring more abstract tasks in response to immigration. Dustmann et al. (2013) shows that recent immigrants start working in occupations offering a much lower wage than natives with similar observable characteristics. Ortega and Verdugo (2014) finds a positive correlation between wages and the immigrant share across cells of education and experience in France using the factor proportion approach of Borjas (2013).

immigration either because the share of immigrants in that industry/occupation is larger or because natives in that group (for example, in the construction sector) are more likely to offer skills similar to those of immigrants, even if they have a different education and experience level.

Such an approach faces important empirical challenges. Indeed, the effect of immigration may not be limited to wages or employment, and immigration inflows may generate a reallocation of natives to other locations (Borjas, 2006) or to different industries or occupations (Peri and Sparber, 2009). If movers and stayers have different characteristics, immigration might affect how native workers are distributed by observed and unobserved skill levels across locations and occupations. For this reason, accounting for these compositional changes is potentially important when assessing the impact of immigration at the location level. Similarly, to get a more complete picture of the impact of immigration, it is important to follow the outcomes over time of location movers and industry/occupation movers, as these might be affected differently than those of the stayers.

To examine these questions, we exploit a large administrative French panel that that allows us to identify the initial location and industry/occupation of native workers and to follow their labour market trajectory over the period 1976-2007. This exceptionally high quality data covers all private sector employees and provides exhaustive and reliable information on the wages, occupation, number of days worked, and geographical location at the municipality level for about 4% of French private sector employees. In contrast to many papers, the large size of our panel allows us to define narrow groups of blue-collar workers using the initial location and industry and thus to isolate the groups of natives that are more likely to be affected. We also rely on very large (25%) sample extracts from the Census to count how many immigrants arrive in each local labour market and to construct an instrumental variable for these regional inflows based on ethnic networks.

Another advantage of using panel data is that we can both assess and control for changes in unobserved heterogeneity of workers within occupations and locations and isolate the causal effect of immigration on wages from any compositional change. In addition, as we track workers over time, we can directly investigate the selection patterns of those who move into a different occupation, industry or location and assess whether they ended up doing better or worse than those who have stayed.

To guide the empirical work, we first describe a simple Roy model à la Gibbons, Katz, Lemieux, and Parent (2005) that provides testable predictions on how the selection of workers across sectors will be affected by labour supply shocks induced by immigration. In such a model, workers' allocation across sectors is governed by comparative advantage as returns to skills are sector specific. These comparative advantages depend on observed and unobserved individual skills. The pressure of immigration on wages in some sectors provides incentives for natives to reallocate across sectors, which in turn changes the distribution of ability across sectors. The model predicts that, depending on the returns to skill in their sector of destination, movers will be either at the top or the bottom of the initial ability distribution. As a result, changes in average wages in a sector caused by an immigrant inflow reflect in part changes in the average ability in the group. The model also predicts that the wage will evolve differently for movers and stayers, as it will depend on differences in returns to skills across sectors for movers.

We examine the implications of this model with the data. To avoid misclassification problems because of the downgrading phenomenon, we do not allocate immigrants into particular skill groups in our empirical specifications. Instead, we examine for different subgroups of blue-collar natives the impact of a local immigration shock on their wage and employment, but also on their choice of location and industry/occupation. We also assess

whether there is evidence of sorting in response to immigrant inflows, i.e. whether those changing location or occupation are systematically different from those that remain.

Regarding geographical mobility, we find compelling evidence in alternative datasets of a positive correlation between immigrant inflows into local labour markets and blue-collar natives' outflows from these markets. Quantitatively, baseline 2SLS estimates suggest that a 10 p.p. increase in the immigration rate[5] raises the outflow rate of blue-collar natives by 9.1 p.p. An important new result is that these outflow rates vary dramatically with the initial industry of the native worker. In particular, we estimate larger displacement effects for workers in the most immigrant-intensive industries such as non-tradable industries and particularly the construction sector.

Second, consistent with Peri and Sparber (2009) for the U.S. or Ortega and Verdugo (2014) for France, we find that blue-collar natives are more likely to change occupation following immigrant inflows. This change is towards better-paid occupations that require less routine tasks, and often to non-blue-collar occupation such as white-collar employee or technician. However, once again, the estimated effect importantly varies with the initial industry/occupation of the worker. In particular, we find much less upgrading for low-skilled blue-collar workers in the construction sector or in the non-tradable sector.

Third, there is also strong evidence that, within groups, workers changing location or occupation are not a random sample of the sending population. Specifically, those moving to occupations with less routine tasks tend to be positively selected, in the sense that they initially had higher wages in the group. In contrast, workers changing location tend to be negatively selected. As selection is positive along one dimension and negative along the other, the overall effect of selection is generally ambiguous.

[5] We define the changes in the immigration rate as the ratio of the increase in the number of immigrants to the initial number of workers in the commuting zone.

In the second part of the paper, we assess how immigration affects labour supply and wages. We find no evidence of a negative impact of immigration on the number of days worked, and this result systematically holds across different subgroups of workers. No negative effect on the employment to population rate is found either.

In contrast, the results indicate that average wages fall in response to immigration, and particularly so for blue-collar natives initially in industries that attracted a large number of immigrants. Overall, we find that an increase in 10 p.p. in the immigration ratio at the local level lowers the average daily wage by 3 log point. Nevertheless, a strong heterogeneity is observed. We find much larger wage decreases for blue-collar natives initially in non-tradable sectors, and particularly so for low-skill construction workers. For this group, an increase in 10 p.p. in the immigration ratio at the local level lowers the wages by 7 log points.[6]

The results also suggest that controlling for composition matters.[7] For some groups, the equivalent cross-sectional estimates –i.e. the estimates with the same data when the longitudinal dimension is not exploited–tend to be significantly larger. There is also substantial evidence that location movers are losing more than others as we obtain larger negative wage effects when the sample includes location movers than when they are excluded. In contrast, the negative effects of immigration are found to be smaller when the sample includes those who have changed occupation or industry after the immigrant inflows.

This paper extends at least three literatures. First, our work confirms that changes in location and occupations are important adjustment channels through which natives adjust to immigrant supply shocks. Unlike previous papers, we show that those changing location and occupation are selected but come from different parts of the wage distribution, implying that

[6] This evidence is consistent with Dustmann and Glitz (2015) that find a more negative wage response in nontradable industries but little effect in tradable or manufacturing industries. Bratsberg and Raaum (2012) points to larger effect of immigration on wages in the construction sector.

[7] This result is consistent with Bratsberg and Raaum (2012) that also found that selective attrition might mask the causal wage impact of immigration using data from the construction sector in Norway.

the bias incurred in a purely cross-sectional analysis can in principle be ambiguous.[8] To the best of our knowledge, we are the first to pinpoint the opposing nature of these selection patterns and assess their implications. Second, our results confirm that, as recently argued by Borjas and Monras (2016), it is crucial to focus on the groups of natives more likely to be affected by the immigrant supply shock.[9] However, unlike most of the previous literature which chose *ex ante* education/experience as the relevant dimension, our identification strategy shows that industry/occupation is a relevant dimension *ex post.* Third, our results indicate that immigration has important distributional consequences, not only between skilled and unskilled workers, as emphasized by most of the literature, but even within homogenous groups of blue-collar workers initially in the same industry, as those that who stay in the same occupation or industry in response to immigration tend to experience larger wage losses.

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

I) Data and descriptive evidence

Data Sources

[8] See also Lull (2014) that provides an interesting evaluation of compositional changes in the native population following immigration using a structural econometric approach.

[9] Cohen-Goldner and Paserman (2011) find that the effect of immigration on wages is concentrated in blue-collar occupations. De New and Zimmermann (1994) find small gains for white-collar employees but larger negative effects for blue-collar workers. Bratsberg, Raaum, Røed and Schøne (2014) find heterogeneous wage effects depending on the country of origin of immigrants. Cattaneo, Fiorio and Peri (2015) find that European workers are more likely to choose occupations associated with higher skills and status. D'Amuri and Peri (2014) show that the reallocation of natives is larger in countries with more flexible labour laws. Foged and Peri (2016) consider the geographical and cross-industry variation in the proportion of immigrants in Denmark, and show that immigration has a positive wage impact on the less skilled natives and encourages them to work in more complex occupations.

Our primary data source is the matched employer-employee panel DADS (*Déclaration Annuelle de Données Sociales*) collected by the French National Institute for Statistics (INSEE).[10] The sample contains earning histories for all individuals born in even-numbered years in October. The DADS panel is available annually from 1976 to 2007 except for 1981, 1983 and 1990 where the data were not collected.

Three features of this dataset make it well-suited for our purposes: first, the data are collected for compulsory fiscal declarations made annually by all employers for each worker and the data are thus considered very reliable.[11] The wage data in particular are considered of very good quality, as the reporting is made by the employer and is used by the tax authorities to calculate the employee's income tax. Employers have no incentives to misreport wages as this is severely punished with fines. Second, since the data are collected for fiscal reasons, attrition has been evaluated to be very low and mostly results from the absence of any work during a year.[12] Third, the sample is very large: we have information on 350,000 individuals per year over the period, amounting to about 4% of employees.[13] The large size of our data guarantees that we have enough observations even for quite narrowly defined groups of workers.

The data contain a unique record for each employee-establishment-year combination. For each job spell, the panel reports earnings, whether the job was part-time or full-time, the number of days of work and the location at the municipality level.[14] We aggregate job spells over the year to obtain the total annual labour earnings and the total annual number of days

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[10] See e.g. Abowd, Kramarz, and Margolis (1999) or Combes, Duranton, and Gobillon (2008) for recent papers using this dataset.

[11] Civil servants and some public sector firms were excluded until the early 1990s. Using data from the French Labor Force Survey, we estimate that they represented approximately 8% of the labour force during the period.

[12] Koubi and Roux (2004) documents that most attrition in the DADS panel corresponds to inactivity or to working outside of the DADS-covered sector (such as self-employment). Attrition in the DADS panel has also been shown to be negligible compared with typical survey-based panels such as the European Community Household Panel (Royer, 2007).

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

[14] Information on whether an employment spell was full or part time is available over the entire period but the number of hours worked is only available after 1993 (see Aeberhardt, Givord, and Marbot, 2012, for a discussion). Following the current practice, as the number of hours is quite noisy, we have chosen not to use it.

worked for each individual. Whenever an individual has worked in several occupations or industries in a given year, the individual is allocated to the industry/occupation of the job held for a longer period of time. A shortcoming of the data is that it does not include information on education. In addition, as the DADS does not supply any detailed information on the nationality of the respondent but reports instead whether the individual is born in France or not, natives are defined as those individuals born in France.[15]

The number of immigrants across labour markets is measured with Census data. We do so for two reasons. First, we have access to 25% extracts of the population (20% in 1975), which renders our estimates immune from attenuation biases as identified in Aydemir and Borjas (2011). Second, unlike the DADS, the Census includes information on the country of origin of immigrants which allows us to construct an instrumental variable for the location choices of immigrants based on differences in the initial settlement patterns across immigrant groups. Censuses of the population took place in 1968, 1975, 1982, 1990, 1999 and 2007. As is conventional, an immigrant is defined as a foreign-born individual who was not French at birth.

Local labour markets are defined using the 2010 definition of commuting zones (*zones d'emploi*) designed by the French Statistical Institute. Commuting zones approximate local labour markets using information on daily commuting patterns. They aggregate the 36,699 French municipalities into 297 labour market regions.[16]

Our empirical study covers the period from 1975 to 2007. We combine information on the employment and wages of natives from the DADS panel with data on the number of

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[15] All individuals born in Algeria before its independence from France in 1962 are reported in the DADS as being born abroad independently on whether they are of European or Arab/Berber origin. For this reason, Europeans born in pre-independence Algeria cannot be 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 natives of French-born citizens who are born abroad is rather small and declining over time: 4.4% and 3.2% in respectively 1982 and 2007.

[16] Commuting zones are defined in a consistent way over time using the municipality identifier. We drop commuting zones from Corsica (less than 0.3% of the population), as a change in the *département* code in 1976 complicates their matching across datasets over time. Commuting zones have been previously used with the DADS panel in Combes et al. (2008) and Combes, Duranton, Gobillon, and Roux (2012).

immigrants at the commuting-zone level obtained from the Census. We only retain years in the sample when both datasets are available. This implies that our regressions exploit medium-run variations in immigration and labour market outcomes over periods of 7 to 9 years.[17]

As the DADS does not contain information for individuals with no labour earnings during a complete year, we are concerned that selective attrition to unemployment or inactivity might bias our results. To minimise these risks, our empirical analysis focuses on prime age men. These workers are the most attached to the labour market and thus non-employment during a full year is less likely to be a major issue.[18] We restrict the sample to male workers aged 25-54. To study how labour market trajectories are affected by immigrant inflows, we focus on changes in outcomes across Census years of workers aged 25 to 45 in census year *t-1* and 32 to 52 or 34 to 54 in census year *t*. We include in the sample all workers that are identified as blue-collar in the initial period *t-1*.

Immigration into France: Key Figures

In 2007, 5.2 million immigrants lived in France, amounting to 8.3% of the population, a smaller proportion than in the US or the UK (respectively 11.5% and 11.9%, see Dustmann et al., 2013, p. 11). While their occupations have diversified over time, Table 1 shows that about 54% of foreign-born workers were in a blue-collar occupation in 2007, a proportion that is 10 p.p. larger than for natives. Foreign-born workers are also twice as likely as natives to work in the construction sector and much more likely to be in unskilled blue-collar occupations.

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

[18] We also apply these restrictions to avoid issues with changes in retirement age over time. Young workers are also eliminated to avoid problems with potentially endogenous labour market participation in case immigration influences educational decisions (Hunt, 2016). Unfortunately, by doing so, we potentially ignore the quite large impact of immigration on the youth labour market (Smith, 2012) and on older workers (Dustmann, Schönberg and Stuhler, 2016b).

Table 2 reports the proportion of foreign born individuals among blue-collar workers for 1976-2007 and for different industries and regions.[19] Foreign-born individuals are over-represented in non-tradable industries relative to tradable industries, and particularly so in the construction sector, where the proportion of foreign workers is larger by 13 p.p than in tradable industries. Across regions, most immigrants are located in large cities in the North, the East and the South while not many have settled in the West and the Centre. For instance, in 2007 only 8% of constructions workers in Brittany were foreign-born, compared to 67% in Paris.

Over the last decades, as in most European countries, the geographical origin of immigrants dramatically changed with the share of European immigrants among immigrants falling from about 60% in 1975 to only 32% in 2007 (Pan Ké Shon and Verdugo, 2015). As a consequence, the share of foreign-born among blue-collar workers rapidly increased in regions that received the largest inflows of non-European immigrants from Africa and Asia. On the other hand, the proportion of immigrants in the workforce fell in regions where most immigrants were originally from Europe, in particular near the Italian and Spanish borders. Table 2 shows the striking differences in the evolution of the share of foreign workers in Paris, which received large inflows of non-European immigrants, and Lyons, where the decline in European immigration has not been compensated by non-European immigration. In the construction sector for example, the share of immigrants increased by 20 p.p. between 1976 and 2007 in Paris while it declined by 12 p.p. in Lyons. Over the period, non-European immigration also increasingly spread to regions with an initially low presence of immigrants, in particular to the West of France. In Brittany for example, the share of immigrants increased by 4 p.p. from 1976 to 2007. This paper exploits these dramatic local variations in the

[19] We rely on standard classification systems of industries. See Appendix for details on industries and occupation classifications used in the paper. Following Hanson and Slaughter (2002) and Dustmann and Glitz (2015), the group of tradable industries includes manufacturing, agriculture, mining, finance and real estate.

inflows of immigrants across regions over the period to identify the impact of immigration across local labour markets.

II) 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). One important distinguishing feature of this model is that workers are heterogeneous in terms of their ability level and comparative advantages determines the allocation of workers in a multi-sector economy.[20] Assume the production function in sector s at period t can be written as $Y_{st} = A_{st} L_{st}^{1-\sigma}$ where Y_{st} is output, L_{st} is the total quantity of labour in the sector, A_{st} is total labour productivity, and $0 < \sigma < 1$. As in Combes et al. (2008), workers (denoted by i) are perfect substitutes but heterogeneous in the number of efficiency units of labour e_{ist} they supply. We abstract from labor supply decisions and each worker provides one unit of labor. As a result, the aggregate amount of labour in sector k is given by $L_{st} = \sum_{i \in J_s} e_{ist}$ where J_s is the set of workers supplying labour in sector s.

Sectors differ in their returns to observed and unobserved characteristics, which generates sorting of workers across sectors. Specifically, we assume that the efficiency units of labour of a type-i worker (e_{ist}) can be decomposed as $\log e_{ist} = X_{it}\phi_s + \eta_s \alpha_i$, where X_{it} is a vector of time-varying observed characteristics of the worker and α_i is the worker's fixed effect unobserved productivity. The terms ϕ_s and η_s capture sector specific returns to respectively observed and unobserved worker characteristics. For simplicity, a higher index s is assigned to a sector the higher the return to unobserved ability $\eta_s > 0$ i.e. $\eta_s > \eta_{s-1}$ for all s.

[20] Our model ignores the potential complementarity/substitutability among groups of workers with different skills which are a key ingredient of the "canonical" model (Dustmann, Schönberg and Stuhler, 2016b). The canonical model analyses the impact of immigration on the labour market with a constant returns to scale production function that combines various types of labour. The model presented here focuses on selection and reallocation and neglects the role of capital adjustment (Dustmann et al., 2013) or the existence of imperfect substitution between groups of workers, in particular natives and immigrants (Ottaviano and Peri, 2012, Manacorda et al. 2012).

With competitive labour markets, the log wage w_{ist} of worker i in sector s in period t is given by the log marginal product of labour:

$$w_{ist} = B_{st} - \sigma \log L_{st} + \eta_s \alpha_i + X_{it}\phi_s , \tag{1}$$

where $B_{st} = \log\left((1-\sigma)A_{st}P_{st}\right)$ and P_{st} is the price of the sector-s good.

Given that the payoffs to ability are sector specific, workers will not be initially indifferent across sectors and, in the absence of mobility costs, they simply choose the sector offering the highest wage given their skills. Conditional on X_{it}, the equilibrium is thus characterised by a set of thresholds denoted $v_s\left(X_{it}\right)$ and an allocation of workers across sectors $(L^*_{1,T},\ldots,L^*_{S,T})$ such that no worker gains by moving to another sector. Thus, individuals choosing to work in sector s are such that their unobserved ability satisfies $v_{s-1}(X_{it}) < \alpha_i < v_s(X_{it})$. Analytically, we get:[21]

$$v_{s-1} = \frac{B_{s-1,t} - B_{s,t} - \sigma\left(\log L^*_{s-1,t} - \log L^*_{s,t}\right) + X_{it}(\phi_{s-1} - \phi_s)}{\eta_s - \eta_{s-1}} , \tag{2}$$

which shows that an exogenous increase in labour supply in any sector s (i.e. a shock to $L_{s,t}$) impacts the allocation of workers across sectors through adjustments in relative wages.

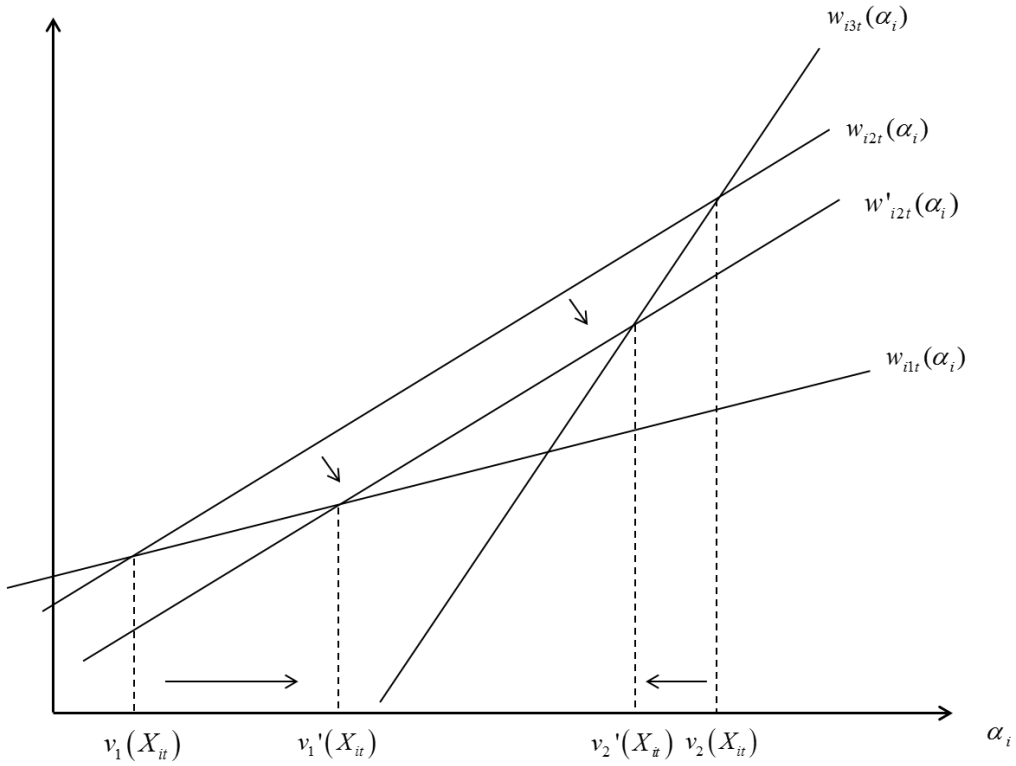
Firms can employ natives N_{st} or immigrants I_{kt}, i.e. $L_{st} = N_{st} + I_{st}$. Consider now an exogenous inflow of immigrants $\Delta I_{s,t}$ into sector s and, assume, as in Borjas (2003), that immigrants are not mobile across sectors. Before any reallocation of natives across sectors has taken place, from (2) the immigration inflow reduces the threshold by $\Delta v_{s-1} \simeq \frac{\sigma}{\eta_s - \eta_{s-1}} \frac{\Delta I_{s,t}}{L_{s,t}}$ and the natives with the highest unobserved productivity in sector $k-1$ move to sector k. Similarly, $\Delta v_s \simeq \frac{-\sigma}{\eta_{s+1} - \eta_s} \frac{\Delta I_{s,t}}{L_{s,t}}$, and the sector-$s$ most productive natives move to sector $s+1$.

[21] We assume that.. $B_{s,t} - \sigma \log L_{st} > B_{s+1,t} - \sigma \log L_{s+1,t}$ .. holds for all s, a necessary condition for workers to be present in all sectors.

Workers changing sectors are clearly not a random sample of the initial group: depending on whether their destination is a sector with higher or lower returns to skills, they originate from either the bottom or the top of the distribution (conditional on X_{it}). To illustrate this, Figure 1 represents a three-sector economy characterised by higher marginal returns to unobserved ability in sector 3 than in sector 2, and in turn in sector 2 than in sector 1. Initially, individuals with $\alpha_i < v_1(X_{it})$ choose sector 1, while those with $v_1(X_{it}) < \alpha_i < v_2(X_{it})$ and $\alpha_i > v_2(X_{it})$ choose respectively sector 2 and sector 3. Consider now an exogenous immigration inflow into sector 2, which results in a fall in the sector-2 wage schedule from $w_{i2t}(\alpha_i)$ to $w_{i2t}'(\alpha_i)$ and initially pushes workers with unobserved ability $v_1(X_{it}) < \alpha_i < v_1'(X_{it})$ away from sector 2 and into sector 1, and workers with unobserved ability $v_2'(X_{it}) < \alpha_i < v_2(X_{it})$ away from sector 2 and into sector 3.

The reallocation of workers attenuates the initial effect of immigration in a sector but affects wages in other sectors even when immigrants concentrate in only one sector. This reallocation will drive down wages both in sector 1 and in sector 3, and in addition raise (resp. lower) the average ability in sector 1 (resp. sector 3). Graphically, the wage schedule in sectors 1 and 3 will move down, while the schedule in sector 2 moves up, until a new equilibrium is reached.

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



The estimation of the effect of immigration on wages is complicated by these endogenous reallocations. From (1), computing the difference of the average sector-s log wages $\overline{w_{st}}$ between t and t-1, we get:

$$\Delta\overline{w_{st}} \equiv \overline{w}_{s,t} - \overline{w}_{s,t-1} = \Delta B_{st} - \sigma \log \frac{L_{st}}{L_{s,t-1}} + \phi_s \Delta \overline{X}_{st} + \eta_s \left(\overline{\alpha}_{s,t} - \overline{\alpha}_{s,t-1} \right) \qquad (3)$$

where $\overline{X}_{st}$ and $\overline{\alpha}_{s,t}$ are respectively the average observable and unobservable individual characteristic in the sector. Defining λ_{st} the labour supply parameter that characterises how native labour supply in the sector adjusts to an immigrant inflows such that

$N_{s,t} = N_{s,t-1} - \lambda_{st} \Delta I_{s,t}$, we get that $\log\left(\frac{L_{s,t}}{L_{s,t-1}}\right) = \log\left(1 + \frac{(1-\lambda_{st})\Delta I_{s,t}}{L_{s,t-1}}\right) \simeq \frac{(1-\lambda_{st})\Delta I_{s,t}}{L_{s,t-1}}$.

Replacing this expression into (3), we get:

$$\Delta\overline{w_{st}} \equiv \Delta B_{st} - \sigma(1-\lambda_{st})\frac{\Delta I_{s,t}}{L_{s,t-1}} + \phi_s \Delta\bar{X}_{st} + \eta_s\left(\bar{\alpha}_{s,t} - \bar{\alpha}_{s,t-1}\right). \qquad (4)$$

The term $\bar{\alpha}_{s,t} - \bar{\alpha}_{s,t-1}$ captures changes in the unobserved productivity of workers in sector s and will generally be different from zero. The direction of the biases related with these unobserved changes in average ability is uncertain as movements from both low- and high-skill workers are possible. The bias also depends on η_s, which determines the returns to specific skills in the sector. Another interesting implication of the model is that the wage loss related with immigration depends on whether an individual changes sector or not. For those changing sector, the wage loss varies with the ability level α_i and differences in returns to ability across sectors η_s.

III) Empirical Implementation

To take equation (4) to the data, we interpret a sector as a location, and estimate the wage effect of immigration on blue-collar natives (or a subset of blue-collar natives from a specific industry/occupation *k*) by using differences in immigrant inflows across local labour markets to identify the model.[22] Following recent work by Dustmann et al. (2013) among others, we avoid classifying immigrant workers across industry/occupation groups and assume thus that the relevant immigration shock for an industry/occupation group is the location-wide ratio of the change in the number of immigrants to the initial population, no matter the initial industry/occupation of the immigrant.[23] We proceed in this way for three reasons extensively discussed in Dustmann, Schönberg and Stuhler (2016b). First, such procedure is immune to any misclassification of immigrants that could arise because of, among other reasons, the

[22] See De la Roca and Puga (2017) for evidence of differences in returns to skills and experience across cities. Selection related to locational migration can also be generated by heterogeneous moving costs of workers across locations as in Moretti (2011) or Beaudry, Doms, and Lewis (2010). See also Borjas (2006) for a model where immigration influences the location choices of natives.

[23] This approach is also followed by Altonji and Card (1991), Dustmann, Fabbri and Preston (2005), Saiz (2007), Boustan, Fishback and Kantor (2010), Smith (2012), Dustmann, Fratini and Rosso (2015) or Mazzolari and Neumark (2012) among others.

"downgrading" phenomenon. Second, it would be very difficult to find a convincing instrument for changes in the number of immigrants in a particular industry/occupation. Third, the estimates are easily interpretable and of direct policy relevance. The parameter identifies the *total* effect of immigration on a particular group of natives, instead of the specific effect of a particular group of migrants. How much immigrants compete with natives in a group will be captured in the estimates of the parameter.[24]

Assuming, as common in the literature, that the tem ΔB_{st} in equation (4) can be captured by a full set of time (γ_t^k) and regional fixed effects (γ_r^k), equation (4) leads to a regression model of the type:

$$\Delta w_{lt}^k = \beta^k \Delta p_{lt} + \nu^k \Delta Z_{lt} + \phi^k \Delta X_{lt}^k + \gamma_t^k + \gamma_r^k + \varepsilon_{lt}^k \tag{5}$$

where Δw_{lt}^k is the change in average log wages in location l between two periods for blue-collar group *k*, Z_{lt} is a vector of locational industry-specific factors varying over time and contains several location and industry specific factors and $\Delta p_{lt} = \frac{\Delta I_{l,t}}{L_{l,t-1}}$ is the immigration shock in the location defined as the ratio of the change in the number of immigrants to the initial population in the location.

The model is estimated by pooling multiple decades across censuses as stacked first differences. Differencing eliminates time-invariant observed or unobserved wage differences across locations that could be correlated with immigration. The specification also includes changes in average individual-level demographic controls of the native population (X_{lt}^k), in

[24] To see this, note that assuming that a share λ^k of immigrants and natives affect labour supply in industry/occupation k, the coefficient β^k is equivalent to $\beta^k = -\sigma(1-e_t^k)\lambda^k$. In other words, the regression coefficient that relates wage changes to the supply shock amalgamates the wage elasticity σ, the labour supply parameter e_t^k and the extent to which an increase in overall immigration affects labour supply in industry/occupation k.

practice changes in the average experience, as well changes in area level controls (Z_{lt}), namely changes in the share of white- to blue-collar workers, the share of workers in construction, and the overall share of workers in manufacturing industries.[25] As in Dustmann and Glitz (2015), Smith (2012), and Borjas and Monras (2016), regressions are weighted by the number of observations used to compute the dependent variable. Specifically, the equations are weighted by $(1/N_{lt}^{k}+1/N_{l,t-1}^{k})^{-1/2}$ where N_{lt}^{k} is the number of individuals from blue-collar group-*k* in location *l* at period *t*.[26]

Definition of the groups

Unlike most previous work, we define groups of blue-collar workers based on their *initial* instead of their contemporary industry/occupation. As a result, for example, when *k* in equation (5) corresponds to the entire sample of blue-collar natives, we follow over time and across locations the changes in outcomes for both those that have remained blue-collar over the period, and for those who have become white collar. Similarly, if *k* refers to the low-skill employees in non-tradable industries, we follow over time and across locations all these workers independently on whether they have moved up the occupational ladder (by becoming a skilled blue-collar or a white collar worker) or they have changed industry.

Also, we test for the differences in the response to immigration by running regression (5) for blue-collar natives as a whole, but also for subsets of blue-collar natives initially in different industries/occupations. Specifically, across industries, we consider in turn the blue-collar workers employed in tradable industries, those employed in non-tradable industries, and those employed in the construction sector. Indeed, as illustrated by Table 2, in 2007 in France, the share of foreign-born workers was twice as large in non-tradable industries than in

[25] These controls are computed using only native workers. A legitimate concern is that these controls are endogenous and should not be included in the regression. In practice, including them does not affect the results as demonstrated in Table 15 and discussed in the robustness section at the end of the paper.

[26] These are the optimal weights in first-differenced cells from micro-level data. This expression is derived from straightforward calculations of the variance of a first-difference variable measured with errors when the measurement error is proportional to the number of observations and is independent across years.

tradable industries, and within non-tradable industries, the proportion of foreign-born was particularly high in the construction sector. We also distinguish blue-collar workers by the skill level of their occupation,[27] and conduct additional separate analyses for the employees who are initially in a low-skill occupation in a non-tradable industry, and in a low-skill occupation in the construction sector. If labour markets are segmented, the supply effect of immigration should vary across industries and skill levels. On the other hand, if blue-collar workers are close to perfect substitutes, then the impact of immigration should be similar across groups.

Identification: accounting for composition effects and endogenous immigrant location choices

Equation (4) makes it clear that changes in average wages within groups reflect both the impact of immigration on the supply of labour and endogenous changes in the unobserved average productivity of workers. Panel data allow us to control directly for changes in unobserved heterogeneity within locations. We adopt the most straightforward way to do this and, as we can follow workers over time, we perform our estimates on a balanced panel that keeps the composition of the sample constant across periods.

In our main specification, we focus on stayers, defined as employees that are classified as belonging to the same blue-collar group *k* in both periods. To assess the importance of sorting, we compare the results of this specification with estimates that also include the employees moving out of group *k*. If movers are included in the sample, average changes in wages in the group are a weighted average of the wage changes of movers and stayers.

A second important issue is that it is very unlikely that immigrants' geographic settlement decisions are exogenous to local labour market conditions. If immigrants settle

[27] In the French occupational classification, skilled blue-collar workers (*ouvriers qualifiés*) include machine operators, mechanics or more generally tradesman while unskilled blue-collar (*ouvriers non-qualifiés*) typically refers to labourers.

disproportionately in areas with better local labour market, then ordinary least squares (OLS) estimates will be biased. Following other studies that use a local labour markets approach, we construct an instrumental variable to deal with this issue. As in Card (2001) and Cortes (2008), we use the initial proportion of co-nationals in the commuting zone to construct an instrument for future immigrant inflows. Specifically, the predicted number of immigrants from country *c* in location *l* is simply given by the total number of immigrants I_{ct} from that country in the Census year *t* multiplied by the proportion of those immigrants (both skilled and unskilled) that were choosing that location in the previous census *t-1*, i.e. $\lambda_{cl,t-1} = \frac{I_{cl,t-1}}{I_{c,t-1}}$.

Adding up across countries of origin, the expected number of immigrants in location *l* is then given by

$$\hat{I}_{lt} = \sum_c \lambda_{cl,t-1} I_{ct} .$$

Given the large sample size, we can exploit the 54 different countries of birth available in the data. Because the endogenous variable is a percentage, our final instrument $\Delta\hat{p}_{lt}$ is defined by using changes in the number of predicted immigrants in the location divided by the initial number of natives, i.e. $\Delta\hat{p}_{lt} = \frac{\hat{I}_{lt} - \hat{I}_{lt-1}}{N_{lt-1}}$.

Table 3 examines how well this instrument predicts changes in the immigrant ratio. Observations correspond to first-differences between census years (i.e., 1975-1981, 1981-1990, 1990-1999, and 1999-2007) for each of the 297 commuting zones. Column (1) reports estimates from a simple bivariate model while column (2) includes a full set of control variables. In both specifications, the coefficient is positive and strongly significant. A comparison between columns (1) and (2) indicates that including additional variables in the model lowers by a third the estimated parameter but also raises the precision of the estimate. With unweighted estimates (column 3), the coefficient diminishes slightly but still remains

statistically significant. The F-statistics[28] are close to or greater than 30 in all cases, thus easily passing the weak instrument test.

IV) Immigrant Inflows and Natives' Mobility Patterns

Before turning to wages and employment, we assess the relevance of mobility across locations and occupations as an additional adjustment channel to immigration.[29]

A. Geographic mobility

Following Card (2001, 2009) or Cortes (2008), we use as a dependent variable the outflow rate defined as $o_{lt}^k \equiv \frac{O_{lt}^k}{N_{l,t-1}^k}$, where O_{lt}^k is the number of group-*k* natives that were in location *l* in Census *t-1* and have moved to a different location by Census *t* and $N_{l,t-1}^k$ is the number of group-*k* natives in location *l* at Census *t-1*. We estimate:

$$o_{lt}^k = \beta^k \Delta p_{lt} + \nu^k \Delta Z_{lt} + \phi^k \Delta X_{lt}^k + \gamma_t^k + \gamma_r^k + \varepsilon_{lt}^k .$$

The first column reports of Table 4 results for a sample including all natives in a blue-collar occupation in the initial period, while the other columns report estimates for different subsamples of blue-collar natives. Both OLS and 2SLS results suggest that blue-collar natives respond to immigrant inflows by changing location. Strikingly, IV estimates are much larger than OLS estimates. These effects are non-negligible: the coefficients indicate that an increase of 10 p.p. in the immigration rate raises the location outflow rate by 9.1 p.p. for blue-collar natives taken as a whole. In addition, this effect is larger when one restricts the analysis to the subsample of blue-collar natives in non-tradable industries (9.7 p.p. increase in the outflow

[28] As we use cluster robust standard errors at the commuting zone level in our regression, we report the Kleibergen-Paap F-stat.

[29] The relationship between local immigrant inflows and native outflows from the commuting zone is currently the focus of a growing literature. Using US decennial data, Card (2001) and Cortes (2008) have found no evidence of native outflows in response to immigrant inflows while Borjas (2006), on the other hand, reports strong displacement effects. More recently, using US annual aggregate data, Wozniak and Murray (2012) find that immigrant inflows are correlated with declines in outflows of low skill natives within a period of one year. Recent European studies found stronger evidence of displacement (see Hatton and Tani, 2005, for he UK, and Mocetti and Porello, 2010, for Italy).

rate) and particularly so for low-skilled blue-collar natives in the construction sector (12.2 p.p. increase).

As noted before, if mobility is observed, an important question is whether movers and stayers have different characteristics, as this would imply that mobility changes the composition of natives across locations and occupations. Our simple sorting model predicts that if the destination sector is characterised by higher (resp. lower) returns to skills, movers should be more (resp. less) skilled than stayers. While different criteria are possible, we adopt a simple approach to study selection by considering the initial location in the wage distribution in the group. Following Borjas (1999), we define positive selection as a situation where, conditional on the occupation and location:

$$E(w_{il,t-1}^{k} \mid \text{movers in t}) > E(w_{il,t-1}^{k} \mid \text{stayers in t})$$

where $w_{il,t-1}^{k}$ is the initial wage level. If there is positive (resp. negative) selection, movers have on average higher (resp. lower) wages than stayers in the initial location. We test for selection by estimating the following specification at the individual level:

$$Move_{ilt}^{k} = \Gamma_1^k \tilde{w}_{il,t-1}^{k} + \Gamma_2^k (\tilde{w}_{il,t-1}^{k} \times \Delta p_{lt}) + \beta^k \Delta p_{lt} + \nu^k \Delta Z_{lt} + \phi^k \Delta X_{lt}^{k} + \gamma_t^k + \gamma_r^k + \varepsilon_{lt}^k$$

where the dependent variable $Move_{ilt}^{k}$ takes the value 1 if the individual i has left location l in period t and $\tilde{w}_{il,t-1}^{k} = w_{il,t-1}^{k} - \bar{w}_{il,t-1}^{k}$ is the deviation from the average log wage in the cell. While β^k captures the effect of immigration on mobility, the parameters Γ_1^k and Γ_2^k test for the selection of movers. The first coefficient indicates how the wages of movers compares to the wages of stayers. The second coefficient tests if the selection patterns vary with immigrant

inflows. Estimation relies on 2SLS using the previously described instrument for Δp_{lt} and the interaction of this instrument with the wage i.e. $\left(\tilde{w}_{il,t-1}^{k} \times \Delta p_{lt}\right)$.[30]

Table 5 provides the results. Within each panel, column 1 and 2 compare the estimates from the baseline model obtained with aggregate and individual level data, respectively. Reassuringly, we observe little difference between the two estimates. Column 3 introduces the initial wage. For all blue-collar workers' subsamples, the results paint a consistent picture: workers that are more likely to leave the location tend to have lower wages with respect to the initial group. We find that an increase of one standard deviation of the initial wage (about 0.32) decreases the probability to change location by 4 p.p. (0.32 x 0.128). Column 4 tests whether the selection pattern varies with immigrant inflows. For most groups, the interaction term is negative and it is statistically significant in half of the sectors, suggesting that immigration reinforces the negative selection of movers.

As noted before, the DADS panel only contains individuals with a positive number of hours worked in a year. Even if we focus on male aged 25-55 to minimise this risk, selective attrition to nonparticipation during a full year could still bias our estimates. To assess the robustness of our results, we use alternative outflows rates that can be estimated with the Census and covering the entire population.[31] As no information on initial occupations is available in the data, we classify workers according to their educational attainment (primary, secondary, high-school, or university graduates).[32]

The results in Table 6 are consistent with previous evidence, as the 2SLS estimates indicate that an increase by 10 p.p. in the immigration rate raises by 15 p.p. and 14 p.p. the

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[30] To account for the fact that Δp_{lt} does not vary at the individual level, we use standard errors clustered at the location by year level in this specification.

[31] Outflows rates can be calculated using retrospective information on the location during the previous census. This information is available at the municipality level.

[32] See the Appendix for details on the construction of these education groups. Note that selection patterns cannot be evaluated from Census data, as wages are not reported.

outflow rate of natives with respectively primary and secondary education. In contrast, no statistically significant correlation is found for more educated workers. Overall, Census data tend thus to confirm our previous results and give us little reason to believe that attrition significantly biases DADS results.

B. Occupational Mobility

A second type of adjustment often emphasised in the literature is that natives reallocate to a different occupation or industry in response to increased competition with immigrants. Next, we examine the evidence for this type of mobility and assess its possible implications by studying the characteristics of movers.

We consider in turn different definitions of occupational change and start in Panel A in Table 7 by defining mobility as the change of industry/occupation between period *t-1* and period *t*. When all blue-collar workers are included in the sample (Column 1), this change corresponds to moving to a white-collar occupation, while when we consider blue-collar-workers initially in specific industry/occupations (Columns 2 to 6), a change may correspond to moving to a white-collar occupation or to a different blue-collar industry/occupation. Column (1) shows that immigration is correlated with a higher probability to change occupation for blue-collar natives. The effects are quite large: 2SLS estimates in the first column indicate that an increase by 10 p.p. of the immigrant rate is associated with a 5 p.p. increase of the probability of not being in a blue-collar job in the following period. At the same time, there are substantial differences across groups and in particular no evidence of an effect on low-skilled blue-collar workers.

In Panels B, C and D, we investigate the leavers' destination occupation using as a dependent variable the probability to become respectively an office clerk, a technician, or a manager. Overall, there is a positive correlation between immigration and blue-collar workers upgrading their occupation, with the correlation being larger for becoming a technician and

lower for becoming an office clerk. At the same time, the effect is smaller when considering only blue-collar natives initially employed in the construction sector.

Another approach in the recent literature has been to measure changes in the characteristics of the occupations through their task contents. Tasks performed in an occupation capture the basic skills required in a particular job (Autor. Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Goos and Manning, 2007).[33] As natives might have a comparative advantage in language and abstract reasoning, they might move to occupations requiring more intensively these tasks, while immigrants might concentrate, at least initially, in routine tasks that require less communication and verbal interaction. In Table 8, we follow Peri and Sparber (2009) and use as a dependent variable changes in the average routine of the occupations of workers between two censuses.[34] To interpret the parameter estimates, we normalise our routine to abstract intensity index to have a standard deviation of one across occupations.

OLS estimates in panel A indicate small coefficients, either positive or negative. In contrast, 2SLS estimates show clear evidence of a decrease in average routine intensity for blue-collar workers in the tradable and non-tradable sector in response to low-skill immigrant inflows. The results nevertheless point, once again, to significant heterogeneities as there is virtually no evidence of an effect on the task contents of workers in the construction sector.

An interesting question is whether the previously observed decrease in routine intensity reflects a change in the quality of occupations performed by blue-collar workers within the initial industry or a move to a non-blue-collar occupation such as technician, employee or manager. Among blue-collar occupations, some noticeable variations in routine

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[33] In our case, these measures are available for 7 sub-categories of blue-collar workers (ex: labourers, machine operators …) and also for 14 other categories (managers, service workers, clerks …).

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

intensity are observed in the data. For example, the lowest routine intensity is reported for "*labourer*" with an index of 0.51 while "*machine operators*" have the highest index with a value of 1.30. To investigate this issue, panel B in Table 8 provides regressions using *cross-sectional* variations for different sets of blue-collar employees. With the exception of the tradable sectors, the coefficients are small and not statistically significant for most groups. This suggests that most of the reduction in routine intensity observed in the balanced sample is driven by workers moving out of the blue-collar category.

As for geographical mobility, we document in Table 9 the selection patterns associated with these changes in task contents. For all subsets of blue-collar employees, we obtain a negative coefficient of the initial wage suggesting that individuals with higher initial wages are more likely to move to occupations with lower routine intensity during the period. For most subsets of blue-collar employees (but not for the construction sector), a higher immigration inflow is associated to a bigger fall in routine intensity. At the same time, the interaction term is not statistically significant: there is no evidence that the selection pattern varies for different levels of immigrant inflows.

In sum, the results presented in this section suggest that changes in locations and occupations are endogenously related to immigrant inflows. However, the response of natives widely differs across different subgroups of blue-collar employees. Importantly, there is no evidence of occupational upgrading for workers in the construction sector. On the other hand, these workers are more likely than others to leave the location in response to immigrant inflows.

An important implication of these results is that the attenuation related to endogenous response varies across groups. The fact that those leaving the location have lower wages will increase the average wages of those who stay via a composition effect. The opposite is true for occupational mobility since those who leave tend to have higher wages. These endogenous

reallocations should bias in opposite directions cross-sectional measures of the impact of immigration on wages in these occupations. We explore these issues in the next section.

V) Adjustments through Employment and Wages

We now turn to the analysis of the impact of immigration on the wages and employment of blue-collar natives using variation across locations and time. We assess the consequences of composition effects and endogenous selection by comparing estimates of the model from two balanced samples: first, we estimate a model (referred to as the 'balanced sample of stayers') restricting the sample to those that remained in the same initial blue-collar group in both periods. As we follow only the same individuals remaining in their initial blue-collar occupation/industry, the estimates are net of composition effects but they do not account for the potential effect of immigration on those who have shifted to a different occupation/industry or location. Second, to take movers into account when estimating the wage impact of immigration, we consider a sample including all individuals initially in the relevant blue-collar sample, independently on whether they have changed industry/occupation or location in the second period. The differences between estimates performed on these two balanced samples depend on the share of movers in the group and their relative wage gains or losses with respect to stayers.

Finally, to test the extent to which composition effects bias -if neglected- the estimates of the impact of immigration on wages, a third model is estimated using cross-sectional variations in the data. Workers in the cross-section sample in the initial period are the same than in the balanced sample. However, cross-sectional variations at the occupational level also reflect changes in the composition of workers as some workers have left or joined the relevant blue-collar group.[35]

[35] To keep the results comparable, as in the balanced sample, we also focus on the observed change in outcomes for workers aged 25-45 in the initial period and 35-55 in the end period but we do not track the same workers over time.

Effects on the number of days worked

Before considering wages, it is important to know how immigration affects the labour supply or the employment probability of natives. We start by estimating the effect of immigration on the number of days worked, using as a dependent variable changes in the average log of annual days of work. In panel A of Table 10, the sample includes all workers initially in the relevant group of blue-collar employees while, in panel B, the sample is restricted to stayers in the initial blue-collar group.

For both samples, we find little evidence that the share of migrants affects the number of days worked. The coefficients of 2SLS models vary in sign depending on the group under consideration but are small and generally statistically insignificant. Similarly, Panel C reports that the 2SLS estimates for the cross sectional sample are all statistically insignificant.

A potential risk for the validity of these results is attrition. Because we use administrative data, we consider attrition to be very small. However, as individuals supplying zero days of work in a year are excluded from the DADS sample, we cannot distinguish attrition from non-participation during a full year. Panel A in Table 11 reconsiders the analysis for the balanced sample by assuming that any individual who is not observed in the second period has left the labour force, i.e. by imputing zero days of work to any of these individuals. Even assuming that this extreme assumption is valid, we still do not find any negative and significant correlation between immigration and days worked. If anything, 2SLS models indicate a positive correlation for blue-collar workers, which is inconsistent with the hypothesis that immigration might decrease the labour supply of natives.

Another way of assessing the employment effect of immigration is to use Census data, which contains labour force status. Panel B in Table 11 reports estimates of the impact of immigration on the employment to population rate as estimated with Census data. As in the previous section, we define groups by educational level, as we have no information on the

initial occupation of workers.[36] Results are consistent with our previous analysis: immigration does not appear to be correlated with a decline in employment for prime-age male workers from different education groups. Parameter estimates are always small, and most of the time statistically insignificant.[37] In sum, these different estimates paint a consistent picture: there is no evidence of an effect of immigration on the number of days worked or on the labour force status of native workers in our sample.

Effects on wages

We next examine the effects of immigration on wages. We start in Table 12 by using as a dependent variable the changes in the average of log daily wages in the location. In Panel A, that includes location and/or industry/occupation movers, the 2SLS estimates are negative and relatively large. Column (1) indicates that for blue-collar workers as a whole, a 10 percentage point increase in the immigration rate is associated with wages lower by 3.2 log point. An important result is that the impact is quite heterogeneous across groups, with much larger negative wage effects on low-skill workers in the non-tradable sector and particularly so in the construction sector. Specifically, for low-skill construction workers, the estimates predict that a 10 p.p. increase in the immigrant ratio lowers wages by 7.3 log points.

In Panel B, we estimate the model on the sample of blue-collar employees who remained in the same location and industry/occupation in both periods. Focusing on stayers generally attenuates the estimated negative effects on wages. Panel C in Table 12 provides results based on cross-sectional variations across occupations. For most groups, the estimated coefficients tend to be larger than those obtained in Panel B.

Clearly, the differences between the balanced sample estimates in panels A and B reflect the inclusion or not of natives who changed location and/or industry/occupation

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

[37] We also estimated a similar model using the initial location of workers –instead of their actual location--to compute the employment rates, and no effect was found.

between two censuses. To disentangle how much the difference between the two estimates is driven by either group, Panel B in Table 13 presents results excluding location movers only while Panel C considers in turn excludes industry/occupation movers only. The results in Panel B unambiguously indicate that excluding those who change location dramatically reduces the negative impact of immigration on wages. In contrast, when the sample excludes those who changed occupation (Panel C), the negative wage effect is much larger. This implies that the wages of location movers are much more negatively affected by immigration than the wages of stayers, while industry/occupation movers experience a smaller variation in their wages.

We draw two main conclusions from these results. First, there is a strong heterogeneity in the estimated effect of immigration across blue-workers depending on their initial industry/occupation. The estimates of the wage effects are four times larger for low-skill workers initially in the construction sector than for blue-collar workers in the tradable sector. Immigration clearly does not affect the wages of blue-collar workers in a similar way and disproportionately affects workers in the non-tradable sector, in particular in the construction sector. Studies using larger groups are likely to miss the strong impact that immigration has on these workers.

A second lesson is that it is important to take into account composition effects and endogenous reallocation, as we find the estimated impact to be larger on the balanced sample that excluded occupation movers. These differences are driven by the larger wage losses of location movers while the effects are strongly attenuated when the sample also includes occupation movers. In contrast, the wage of industry/occupation movers is much less affected than the wage of stayers. This implies that there are significant differences in the wage impact of immigration even across workers initially in the same industry/occupation and location.

Robustness

Table 14 examines the sensitivity of the results to the specifications of the baseline model. Indeed, one issue with our instruments might be that the lagged distribution of immigrants is correlated with persistent trends in economic dynamism across locations. As a result, the exclusion restriction of our instrument might not be perfectly valid. A simple test of this hypothesis is to check whether the estimates change in an important way when we exclude different sets of control variables.[38] If the estimates significantly changed, this would indicate that the immigrant inflows predicted by our instrument, which should be orthogonal to other local labour market shocks, are strongly correlated with other factors influencing wages across locations. Specifically, Panel A examines the robustness of estimates using the balanced panel while Panel B reports cross-section estimates. This is done in rows 1 and 2 which respectively include no control (except for time dummies), and regional trends and time dummies. As the estimates are very similar to the baseline results (see Table 12), these patterns are not consistent with the hypothesis that our instrument might be correlated with unobserved determinants of wage changes across locations.

Next, we investigate the extent to which the results might be driven by large cities such as Paris, Marseilles or Lyons, which attract a disproportionate share of immigrants. Row 3 presents estimates where the 3 largest commuting zones have been excluded from the sample while row 4 reports unweighted regressions. Results are broadly similar in these two models except for the group of low-skill construction workers for whom estimates tend to become smaller and more imprecise.

Panel B reports the same robustness tests performed using the cross-section sample. We also find the baseline results to be reasonably robust across most specifications but the

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

precision of the estimates dramatically diminishes in some specifications for low-skill construction workers.

VI) Discussion

In this paper, we have revisited the impact of immigration on the labour market outcomes of natives, focusing specifically on those with (initially) blue-collar occupations. Our rich panel dataset has provided us with a unique opportunity to investigate whether the impact of immigration is heterogeneous across different industries/occupations and also to assess the extent of the potential composition effects underlying the standard cross-sectional analysis.

We have outlined the importance and the consequences of endogenous mobility across local labour markets, occupations and industries in response to immigrant inflows. Our findings show that immigrant inflows are correlated with both native outflows, and with a reallocation of natives to occupations with less routine tasks. While location-movers tend to be negatively selected from the sending population, those moving to occupations with less routine tasks tend to be positively selected.

Importantly, our results point to a strong heterogeneity across and within industry/occupation groups. The wages of blue-collar natives initially in the tradable sector are less affected by immigrant inflows and these workers are also more likely to change occupation in response to immigration than their counterparts in the non-tradable sectors. At the other extreme of the spectrum, low-skill construction workers experience a large wage decrease and tend not to move to a different occupation in response to immigrant inflows. Interestingly, the consequences of immigration are also heterogeneous even within groups, with natives moving occupation (resp. location) experiencing lower (resp. larger) wage decreases.

There are however several limitations to our analysis. First, because we wanted to minimise the risks that our results might be biased by non-participation, we have focused on

prime-aged male workers. According to recent work from Smith (2012), low-skill immigrants might also affect disproportionately younger workers that were not included in our analysis. Similarly, we did not include women in our analysis as the treatment of labour market participation creates an additional complexity for this group. An evaluation of the impact of immigration on young workers and women would be of substantial interest for future work.

Appendix

Data appendix

Occupations: The DADS contains information on 27 different categories of occupations before 1983 and 36 categories afterward. The category "*Blue-collar workers*" aggregates 7 distinct categories of occupations over the period. We merge these occupations with tasks intensity indexes from Goos et al. (2010, Table 4 p.49) based on the Occupational Information Network (ONET) database.

Crosswalk tables for industry classifications: We use the industry classification which remained unchanged for the longest period of time in the data. The NAP (*Nomenclatures d'Activités et de Produits 1973*) is used in the 1975, 1982 and 1990 censuses and in the DADS until 1993. We have created crosswalk tables with other industry classifications to match them with the NAP at the four digit level. The NAF (*Nomenclature d'Activité Française*) is used in the 1999 Census and in the DADS from 1993 to 2002. For the match between NAP and NAF, we have used the 1994 LFS (*Enquête emploi*) in which both codes are given to establish a match at the four digit levels. Similarly, when several possibilities existed, we have kept the most frequent correspondence. In both cases, the match has been completed manually to include exhaustively all codes in the correspondence table at the four digit level.

Education in Census data: The education variable reported in the Census indicates the diploma received by the individual. We use the variable *DIP* in the 1968, 1975 and 1982 censuses, *DIPL1* in the 1990 Census and *DIPL* in the 1999 Census. We classify individuals in

four groups: Primary education, Secondary education, High School and College. Primary education level includes individuals which declare to have no diploma and people having the primary school certificate. Secondary education level includes individuals which report to have a diploma of a level equivalent to the *Diplôme National du Brevet* (BEPC) and includes individuals holding a CAP or a BEP. High school education includes individuals who have a diploma equivalent to the Baccalaureate. This group also includes general, professional or technical Baccalaureate graduates. College level includes all individuals with a diploma of a level superior to the Baccalaureate.

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Tables

Table 1 : Share of blue-collar workers among French and Foreign-born workers, Males aged 25-54

Blue-collar group	1976	1982	1990	1999	2007
	A. Share among French				
All	63.2	59.9	49.5	46.5	45.4
Skilled	37.5	38	36.8	33.8	33.3
Low-skilled	25.7	21.9	12.7	12.7	12.1
All tradable industries	32.1	29	21.9	19.8	17.3
All non-tradable industries (including construction)	31.1	30.9	27.6	26.7	28.1
Construction	12.7	11.2	8.5	7.1	7.7
	B. Share among Foreign-born				
All	82.6	75.5	58.6	53.2	54.4
Skilled	44.1	43.8	40.4	36.1	35.3
Low-skilled	38.5	31.7	18.2	17.1	19.1
All tradable industries	31.9	28.8	19.8	16	12.3
All non-tradable industries (including construction)	50.7	46.7	38.8	37.2	42.1
Construction	32.6	25.3	17.9	13.9	14.5

Source: DADS Panel. Notes: This table indicates the share of different groups of blue-collar workers among the total number of French (Panel A) or Foreign-born (Panel B) workers. The group of tradable industries includes manufacturing, agriculture, mining, finance and real estate. Skilled blue-collar workers include machine operators, mechanics or tradesman while low-skill blue-collar typically refers to labourers.

Table 2: Share of Foreign-born individuals among blue-collar workers in selected industries and regions, 1976-2007, Males aged 25-55

	1976	1982	1990	1999	2007
All blue-collar					
France	20.6	18.7	16.0	14.2	15.8
Paris	32.5	33.9	37.2	41.4	44.9
Lyons	33.5	30.2	28.2	25.8	25.7
Brittany	2.8	3.2	2.7	3.2	5.5
Blue-collar in tradable sector					
France	16.5	15.4	12.9	10.6	9.6
Paris	27.9	28.2	31.9	38.7	39.4
Lyons	27.2	28.5	20.9	21.9	17.1
Brittany	1.3	1.9	2.0	2.1	3.2
Blue-collar in non-tradable sector					
France	24.4	21.6	18.5	16.8	18.9
Paris	34.4	35.9	39.4	44.0	49.6
Lyons	36.8	31.1	30.9	27.1	28.7
Brittany	3.6	3.9	3.2	3.8	6.8
Blue-collar in construction sector					
France	33.8	29.3	25.3	22.1	22.8
Paris	46.6	43.8	48.8	52.4	67.4
Lyons	48.7	41.5	41.2	36.2	35.9
Brittany	4.5	4.9	3.9	5.4	8.4

Source: DADS Panel. All figures refer to blue-collar workers. The group of tradable industries includes manufacturing, agriculture, mining, finance and real estate. Paris and Lyons refer to the commuting zone including the municipalities of these cities while Brittany refers to the entire region.

Table 3: First Stage Results

	Dependent variable : *Change in Immigrant Ratio* Δp_{lt}			
	(1)	(2)	(3)	(4)
Predicted change	0.233***	0.170***	0.171***	0.141***
	(0.041)	(0.037)	(0.036)	(0.032)
First Stage F-stat	31.8	21.2	22.5	18.8
R-squared	0.15	0.38	0.39	0.28
Region fixed effect	No	Yes	Yes	Yes
Period fixed effects	No	Yes	Yes	Yes
Controls for labour force composition	No	No	Yes	Yes
Weight	Yes	Yes	Yes	No

Notes: Data are from the five Census taking place between 1975 and 2007. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include a full set of regions and time fixed effects. Additional controls included in the regressions when indicated. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$ except when indicated otherwise. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5% level, and 1% level.

Table 4: Impact of Immigration on Native Outflows from the Commuting Zone

	Dependent variable: *Outflow rate from the commuting zone between t-1 and t*					
	Sample group under consideration among male blue-collar workers 25-45 in *t-1*, 35-55 in *t*:					
	All blue-collar	Blue-collar in Tradable Industry	Blue-collar in non-Tradable Industry	Blue-collar in Construction Sector	Low-skill blue-collar in Non-tradable industry	Low-Skill blue-collar in construction sector
	OLS					
Δp_{lt}	0.367***	0.374***	0.299***	0.356***	0.357***	0.365***
	(0.086)	(0.088)	(0.087)	(0.102)	(0.092)	(0.113)
	2SLS					
Δp_{lt}	0.913***	0.767***	0.970***	1.050***	1.100***	1.218***
	(0.152)	(0.159)	(0.170)	(0.204)	(0.216)	(0.246)
Baseline rate	0.20	0.14	0.25	0.22	0.25	0.31

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include a full set of regions and time fixed effects. Additional controls included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$. (*), (**), and (***) denote statistical significance at, respectively, 10%, 5% level, and 1% level.

Table 5: Selection in Native Outflows from Commuting Zone

	Dependent variable: *Outflow from the commuting zone probability between t/t-1*							
	Sample group under consideration among male blue-collar workers 25-45 in *t-1*, 35-55 in *t*:							
	A. All Blue-Collar				B. Blue-collar in Tradable Industry			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Δp_{lt}	0.913***	0.932***	0.926***	0.975***	0.767***	0.549**	0.527*	0.580**
	(0.152)	(0.239)	(0.244)	(0.239)	(0.159)	(0.274)	(0.278)	(0.278)
Wage (t-1)			-0.128***	-0.114***			-0.108***	-0.101***
			(0.005)	(0.007)			(0.011)	(0.010)
Wage(t-1) x Δp_{lt}				-0.954***				-0.957
				(0.288)				(0.808)
N	1,188	313,381	313,381	313,381	1,188	141,891	141,891	141,891
	C. Blue-Collar in Non-Tradable Industry				D. Blue-Collar in Construction Sector			
Δp_{lt}	0.970***	0.996***	0.905***	0.929***	1.050***	1.050***	1.068***	1.321***
	(0.170)	(0.262)	(0.263)	(0.256)	(0.204)	(0.218)	(0.224)	(0.257)
Wage (t-1)			-0.105***	-0.083***			-0.085***	-0.063***
			(0.005)	(0.007)			(0.014)	(0.014)
Wage(t-1) x Δp_{lt}				-1.141***				-2.735***
				(0.307)				(0.867)
N	1,188	171,484	171,484	171,484	1,188	54,586	54,586	54,586
	E. Low-Skilled Blue-Collar in Non-Tradable Industry				F. Low-Skilled Blue-Collar in Construction Sector			
Δp_{lt}	1.100***	1.185	1.113	1.134*	1.218***	1.217***	1.213***	1.292***
	(0.216)	(0.346)	(0.338)	(0.323)	(0.246)	(0.510)	(0.502)	(0.514)
Wage (t-1)			-0.081***	-0.075***				-0.085***
			(0.005)	(0.006)				(0.018)
Wage(t-1) x Δp_{lt}				-0.354				-2.240
				(0.336)				(1.229)
N	1,188	81,223	81,223	81,223	1,188	25,439	25,439	25,439

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census Data. Regression (1) in each subpanel is conducted at the commuting zone*time level. The rest of the regressions are conducted at the individual level. All regressions include a full set of regions and time fixed effects and are estimated with 2SLS. Additional controls included in the regressions. Standard errors are clustered at the commuting zone level in column 1 and at the commuting zone by year level in other columns. (*), (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.

Table 6: Impact of Immigration on Native Outflows from Commuting Zone

	Dependent variable: Outflow from commuting zone between period t-1 and t, for different educational levels			
	Primary Education	Secondary Education	High-School	University
	OLS			
Δp_{lt}	0.154	0.171	-0.212	-0.182
	(0.102)	(0.122)	(0.151)	(0.204)
	2SLS			
Δp_{lt}	1.522***	1.406***	0.398	-0.355
	(0.341)	(0.437)	(0.531)	(1.308)

Notes: All data are from the Census. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include a full set of regions and time fixed effects. Additional controls included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$. (*), (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.

Table 7: Impact of Immigration on Natives' Mobility to a Different Industry/Occupation

	Sample group under consideration among blue-collar male employees aged 25-45 in t-1, 35-55 in t					
	All Blue-Collar	Blue-Collar in Tradable Industry	Blue-Collar in non-Tradable Industry	Blue-Collar in Construction Sector	Low-Skilled Blue Collar in Non-tradable Industry	Low-Skilled Blue-Collar in Construction Sector
A. Dependent variable : *Share of workers in a different occupation and/or industry in t*						
	OLS					
Δp_{lt}	0.280***	0.356***	0.179***	0.123**	0.117*	0.086
	(0.056)	(0.087)	(0.040)	(0.055)	(0.062)	(0.117)
	2SLS					
Δp_{lt}	0.495***	0.591***	0.286***	0.242*	0.297*	-0.021
	(0.093)	(0.156)	(0.081)	(0.136)	(0.127)	(0.246)
Baseline Rate	0.21	0.30	0.30	0.32	0.38	0.36
B. Dependent variable: *Share of workers who are office clerks in t*						
	OLS					
Δp_{lt}	0.063**	0.024	0.067***	0.022	0.077**	-0.006
	(0.018)	(0.018)	(0.020)	(0.016)	(0.035)	(0.030)
	2SLS					
Δp_{lt}	0.062*	0.037	0.062***	-0.043	0.026	-0.136*
	(0.034)	(0.046)	(0.019)	(0.041)	(0.062)	(0.079)
Baseline Rate	0.06	0.04	0.07	0.03	0.07	0.04
C. Dependent variable: *Share of workers who are technicians in t*						
	OLS					
Δp_{lt}	0.135***	0.151***	0.152***	0.105*	0.183***	0.157***
	(0.026)	(0.037)	(0.026)	(0.041)	(0.029)	(0.062)
	2SLS					
Δp_{lt}	0.256***	0.220**	0.277***	0.196**	0.381***	0.280***
	(0.058)	(0.087)	(0.056)	(0.086)	(0.064)	(0.106)
Baseline Rate	0.10	0.10	0.09	0.07	0.10	0.08
D. Dependent variable : *Share of workers who are managers in t*						
	OLS					
Δp_{lt}	0.079***	0.098***	0.062***	0.046**	0.076***	0.033
	(0.022)	(0.034)	(0.019)	(0.020)	(0.028)	(0.036)
	2SLS					
Δp_{lt}	0.195***	0.273***	0.127***	0.104***	0.164***	0.072
	(0.042)	(0.073)	(0.033)	(0.036)	(0.049)	(0.046)
Baseline Rate	0.04	0.04	0.04	0.03	0.03	0.02

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level and use 1,188 observations. All regressions include a full set of regions and time fixed effects. Additional controls included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt} + 1/N_{klt-1})^{-1/2}$. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 8: Impact of Immigration on Average Routine Task Content

Dependent variable: *Change in average routine task between t-1 and t*						
	Sample group under consideration among blue-collar male employees aged 25-45 in t-1, 35-55 in t:					
	All Blue-Collar	Blue-Collar in Tradable Industry	Blue-Collar in non-Tradable Industry	Blue-Collar in Construction Sector	Low-Skilled Blue-Collar non-Tradable-Industry	Low-Skilled Blue-Collar in Construction Sector
	A. Balanced sample					
	OLS					
Δp_{lt}	-0.329***	-0.383**	-0.325***	-0.194	-0.393***	0.113
	(0.099)	(0.170)	(0.100)	(0.130)	(0.129)	(0.252)
	2SLS					
Δp_{lt}	-1.270***	-1.474***	-0.946***	-0.224	-1.514***	-0.601
	(0.339)	(0.570)	(0.310)	(0.416)	(0.436)	(1.105)
Baseline Rate	-0.31	-0.31	-0.32	-0.23	-0.32	-0.25
	B. Cross-section sample					
	OLS					
Δp_{lt}	0.033	0.046	0.028	-0.006	0.082	-0.026
	(0.038)	(0.054)	(0.046)	(0.049)	(0.074)	(0.106)
	2SLS					
Δp_{lt}	-0.234*	-0.502*	0.067	-0.002	0.169	-0.262
	(0.131)	(0.232)	(0.113)	(0.167)	(0.242)	(0.476)

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include a full set of regions and time fixed effects. Additional controls are included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$. (*), (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.

Table 9: Selection in Change of Routine Intensity

Dependent variable: Change in routine intensity of the occupation								
	Group under consideration among male blue-collar employees aged 25-45 in *t-1*, 35-55 in *t*:							
	A. All Blue-Collar				B. Blue-Collar in Tradable Industry			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Δp_{lt}	-1.270***	-0.976**	-0.997**	-1.009**	-1.474***	-1.514***	-1.598***	-1.607***
	(0.339)	(0.261)	(0.258)	(0.275)	(0.570)	(0.439)	(0.427)	(0.428)
Wage (t-1)			-0.297***	-0.300***			-0.496***	-0.497***
			(0.009)	(0.007)			(0.016)	(0.018)
Wage(t-1) x Δp_{lt}				0.198				0.133
				(0.531)				(0.918)
N	1,188	313,381	313,381	313,381	1,188	141,891	141,891	141,891
	C. Blue-Collar in Non-Tradable Industry				D. Blue-Collar in Construction Sector			
Δp_{lt}	-0.946***	-0.988***	-0.970***	-0.969***	-0.224	-0.370	-0.305	-0.402
	(0.310)	(0.219)	(0.214)	(0.235)	(0.416)	(0.308)	(0.323)	(0.353)
Wage (t-1)			-0.195***	-0.194***			-0.286***	-0.293***
			(0.009)	(0.009)			(0.012)	(0.024)
Wage(t-1) x Δp_{lt}				-0.014				0.980
				(0.554)				(0.704)
N	1,188	171,484	171,484	171,484	1,188	54,586	54,586	54,586
	E. Low-Skilled Blue-Collar in Non-Tradable Industry				F. Low-Skilled Blue-Collar in Construction Sector			
Δp_{lt}	-1.514***	-1.136***	-1.129***	-1.111***	-0.601	-0.862	-0.865	-0.876
	(0.436)	(0.306)	(0.308)	(0.326)	(1.105)	(0.592)	(0.598)	(0.645)
Wage (t-1)			-0.023***	-0.018**			-0.105***	-0.106***
			(0.009)	(0.010)			(0.019)	(0.019)
Wage(t-1) x Δp_{lt}				-0.274				0.205
				(0.488)				(1.577)
N	1,188	81,223	81,223	81,223	1,188	25,439	25,439	25,439

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census Data. Regression (1) in each subpanel is conducted at the commuting zone*time level. The rest of the regressions are conducted at the individual level. All regressions include a full set of regions and time fixed effects and are estimated with 2SLS. Additional controls included in the regressions. Standard errors are clustered at the commuting zone level in column 1 and at the commuting zone by year level in other columns. (*), (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.

Table 10: Impact of Immigration on Number of Days Worked

Dependent variable : change in log average days of work t/t-1						
	Group under consideration among male blue-collar employees aged 25-45 in *t-1*, 35-55 in *t*:					
	All Blue-Collar	Blue-Collar in Tradable Industry	Blue-Collar in non-Tradable Industry	Blue-Collar in Construction Sector	Low-Skilled Blue Collar in Non-tradable Industry	Low-Skilled Blue-Collar in Construction Sector
	A. Balanced Sample including Location and Occupation or Industry movers					
	OLS					
Δp_{lt}	0.062***	0.022	0.065**	0.118***	0.030	0.133
	(0.017)	(0.021)	(0.023)	(0.037)	(0.066)	(0.130)
	2SLS					
Δp_{lt}	0.021	0.177**	-0.112	-0.057	-0.098	-0.036
	(0.065)	(0.086)	(0.088)	(0.156)	(0.252)	(0.502)
	B. Balanced Sample of Stayers					
	OLS					
Δp_{lt}	0.046***	0.025	0.042	0.045	-0.151	0.075
	(0.015)	(0.019)	(0.024)	(0.038)	(0.096)	(0.088)
	2SLS					
Δp_{lt}	0.007	0.107	-0.052	-0.053	0.099	0.426
	(0.060)	(0.068)	(0.078)	(0.154)	(0.263)	(0.260)
	C. Cross-Section Variations					
	OLS					
Δp_{lt}	-0.028	0.013	-0.051	0.058	-0.159*	0.059
	(0.027)	(0.030)	(0.038)	(0.046)	(0.087)	(0.148)
	2SLS					
Δp_{lt}	0.059	-0.084	0.188*	0.022	0.338	0.394
	(0.071)	(0.110)	(0.101)	(0.140)	(0.224)	(0.534)

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include a full set of regions and time fixed effects. Additional controls are also included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$. (*), (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.

Table 11: Additional Evidence on the Impact of Immigration on Employment

	A. Balanced Sample including Location and Occupation movers : Zero imputed if missing in t Dependent variable: change in average number of days worked t/t-1					
	All Blue-Collar	Blue-Collar in Tradable Industry	Blue-Collar in non-Tradable Industry	Blue-Collar in Construction Sector	Low-Skilled Blue Collar in Non-tradable Industry	Low-Skilled Blue-Collar in Construction Sector
	2SLS					
Δp_{lt}	0.615**	0.957**	0.102	0.227	0.193	0.405
	(0.261)	(0.460)	(0.222)	(0.277)	(0.359)	(0.814)

	B. Census Data Evidence: Dependent Variable: Change in Employment/Population Rate t/t-1			
	Primary Education	Secondary Education	High-School	University
	2SLS			
Δp_{lt}	0.044	0.215	0.635*	0.116
	(0.617)	(0.277)	(0.326)	(0.126)

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include a full set of regions and time fixed effects. Additional controls are also included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$. A (*) denotes statistical significance at the 10% level, a (**) denotes at the 5% level, a (***) at the 1% level.

Table 12: Impact of Immigration on Wages

Dependent variable : change in average log daily wages t/t-1						
	Group under consideration among male blue-collar employees aged 25-45 in *t-1*, 35-55 in *t*:					
	All Blue-Collar	Blue-Collar in Tradable Industry	Blue-Collar in non-Tradable Industry	Blue-Collar in Construction Sector	Low-Skilled Blue Collar in Non-tradable Industry	Low-Skilled Blue-Collar in Construction Sector
	A. Balanced Sample including Location and Occupation or Industry movers					
	OLS					
Δp_{lt}	0.004	0.083*	-0.112	-0.096	-0.228	-0.584*
	(0.043)	(0.049)	(0.072)	(0.131)	(0.144)	(0.319)
	2SLS					
Δp_{lt}	-0.328***	-0.276***	-0.318***	-0.585**	-0.299	-0.733**
	(0.111)	(0.157)	(0.114)	(0.232)	(0.272)	(0.338)
	B. Balanced Sample of Stayers					
	OLS					
Δp_{lt}	0.059	0.009	0.055	0.132*	0.103	0.113
	(0.037)	(0.048)	(0.151)	(0.077)	(0.100)	(0.139)
	2SLS					
Δp_{lt}	-0.212**	-0.283*	-0.354***	-0.578**	-0.806***	-0.655*
	(0.100)	(0.155)	(0.126)	(0.268)	(0.307)	(0.372)
	C. Cross-Sectional Variations					
	OLS					
Δp_{lt}	-0.130*	-0.013	-0.278***	-0.078	-0.634***	-0.274
	(0.069)	(0.061)	(0.095)	(0.139)	(0.173)	(0.313)
	2SLS					
Δp_{lt}	-0.354***	-0.433***	-0.375***	-0.589***	-0.603**	-0.784
	(0.122)	(0.189)	(0.123)	(0.225)	(0.251)	(0.645)

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include a full set of regions and time fixed effects. Additional controls are included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$ where N_{klt} represents the size of the occupation group k in location l and year t. (*), (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.

Table 13: Effect of Including Movers in the Sample

Dependent variable : change in average daily wages t/t-1						
	Group under consideration among male blue-collar employees aged 25-45 in *t-1*, 35-55 in *t*:					
	All Blue-Collar	Blue-Collar in Tradable Industry	Blue-Collar in non-Tradable Industry	Blue-Collar in Construction Sector	Low-Skilled Blue Collar in Non-tradable Industry	Low-Skilled Blue-Collar in Construction Sector
	A. Balanced Sample including Location and Occupation or Industry movers					
Δp_{lt}	-0.328***	-0.276***	-0.318***	-0.585**	-0.299	-0.733**
	(0.111)	(0.157)	(0.114)	(0.232)	(0.272)	(0.338)
	B. Balanced Sample without Location Movers					
Δp_{lt}	-0.205**	-0.069	-0.320***	-0.578**	-0.282	-0.307
	(0.096)	(0.144)	(0.123)	(0.241)	(0.223)	(0.303)
	C. Balanced Sample without Occupation or Industry Movers					
Δp_{lt}	-0.387***	-0.372**	-0.442***	-0.668**	-0.545*	-0.848
	(0.123)	(0.156)	(0.122)	(0.268)	(0.285)	(0.642)
	D. Balanced Sample of Stayers					
Δp_{lt}	-0.212**	-0.283*	-0.354***	-0.578**	-0.806***	-0.655*
	(0.100)	(0.155)	(0.126)	(0.268)	(0.307)	(0.372)

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level and use 1,188 observations (279 locations in four years). All regressions include additional controls. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$ where N_{klt} represents the size of the occupation group k in location l and year t. (*), (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.

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Table 14: Sensitivity of the Effects of Immigration on Average Daily wages to alternative specifications

Dependent variable : change in average daily wages t/t-1							
	Group under consideration among male blue-collar employees aged 25-45 in *t-1*, 35-55 in *t*:						
	All Blue-Collar	Blue-Collar in Tradable Industry	Blue-Collar in non-Tradable Industry	Blue-Collar in Construction Sector	Low-Skilled Blue Collar in Non-tradable Industry	Low-Skilled Blue-Collar in Construction Sector	N
	A. Balanced Sample including location and occupation or industry movers						
1. No covariates	-0.315***	-0.235**	-0.344***	-0.545***	-0.275	-0.669**	1188
	(0.089)	(0.098)	(0.094)	(0.163)	(0.195)	(0.324)	
2. Covariates	-0.316***	-0.250	-0.349***	-0.656***	-0.353	-0.727	1188
	(0.112)	(0.157)	(0.117)	(0.248)	(0.279)	(0.531)	
3. Exclude largest cities	-0.311***	-0.227	-0.271***	-0.218	-0.232	-0.186	1176
	(0.110)	(0.141)	(0.100)	(0.154)	(0.219)	(0.437)	
4. Without weights	-0.438**	-0.339	-0.343**	-0.115	-0.511	-0.359	1188
	(0.178)	(0.213)	(0.169)	(0.210)	(0.428)	(0.582)	
	B. Cross-sectional sample						
1. No covariates	-0.309***	-0.365***	-0.322***	-0.459***	-0.457***	-0.660**	1188
	(0.076)	(0.109)	(0.076)	(0.132)	(0.156)	(0.338)	
2. Covariates	-0.320***	-0.389**	-0.395***	-0.608***	-0.659***	-0.253	1188
	(0.120)	(0.185)	(0.126)	(0.236)	(0.234)	(0.633)	
3. Exclude largest cities	-0.311***	-0.227	-0.271***	-0.218	-0.232	-0.186	1176
	(0.110)	(0.141)	(0.100)	(0.154)	(0.219)	(0.437)	
4. Without weights	-0.459**	-0.675**	-0.473**	-0.466	-0.527	-0.581	1188
	(0.206)	(0.323)	(0.229)	(0.314)	(0.377)	(0.727)	

Notes: All data are from the DADS 1976-2007 except for the immigration inflow and the instrument, coming from Census data. All regressions are conducted at the commuting zone*time level. All regressions include a full set of regions and time fixed effects and are estimated with 2SLS. Additional controls are included in the regressions. Standard errors are clustered at the commuting zone level. Regressions are weighted by $(1/N_{klt}+1/N_{klt-1})^{-1/2}$ where N_{klt} represents the size of the occupation group k in location l and year t *, (**), and (***) denote statistical significance at respectively the 10%, 5% level, and 1% level.