Immigration and Worker-Firm Matching*

Gianluca Orefice (University of Paris-Dauphine, PSL and CEPII)†

Giovanni Peri (University of California, Davis and NBER)‡

April 7, 2022

Abstract

The matching between firms and workers is an important determinant of wages in labor markets. Positive correlation between firms and workers' productivity, called positive assortative matching, increases average wage and the wage dispersion. Using French employer-employee data over the period 1995-2005 we find that increases in immigrant employment, driven by differential historical networks in local labor markets, was associated with stronger positive assortative matching between workers and firms, higher average wages, higher average profits, and higher wage dispersion. We show several pieces of evidence suggesting that an important channel for this effect is increased screening intensity by firms when there is a larger share of immigrants in the labor force, resulting in high quality firms hiring more high quality workers.

Key Words: Matching, Workers, Firms, Immigration, Productivity.

JEL Codes: F16, J20, J61.

---

*We are grateful to Frederic Docquier, Lionel Fontagné, Parag Mahajan, Hillel Rapoport, Ariell Reshef, Gonzague Vannoorenberghe and participants to seminars held at University of Paris 1, Cergy-Pontoise, IESEG, Paris School of Economics, Université Catholique de Louvain, Paris-Dauphine, ZEW Mannheim, Bank of Sweden, OECD-CEPII Migration conference and Royal Economic Society for insightful comments. We acknowledge financial support from the French National Agency for Research, project NaWaCC. Access to the confidential data used in this work has been made possible within secure environment offered by CASD - Centre d'accès sécurisé aux données (Ref. ANR-10-EQPX-17).

†Department of Economics University of Paris-Dauphine, Place du Maréchal de Lattre de Tassigny, 75016 Paris. Email: gianluca.orefice@dauphine.psl.eu.

‡Department of Economics UC Davis, One shield Avenue, Davis CA 95616. Email: gperi@ucdavis.edu

1 Introduction

Recent research has shown that the quality (productivity) of firms explains a significant portion of the wage differentials among similar workers (matched with different firms) and their changes in the recent decades (Abowd, Kramarz and Margolis 1999; Bernard, Jensen, Redding and Schott 2007; Card, Heining and Kline 2013). Additionally, regional economists have shown that local characteristics, such as employment density, may affect firms' productivity and translate in local wage premia (e.g. Glaeser and Mare 2001; Combes, Duranton and Gobillon 2008; and De La Roca and Puga 2017). Local characteristics may also affect how workers and firms are matched with each other, with important consequences for local wages, profits and their dispersion. In particular, some local features may facilitate Positive Assortative Matching (PAM hereafter), namely the matching of high-quality workers with high-productivity firms and low-productivity workers with low-productivity firms. This, in the presence of productive complementarities between workers and firms' quality, generates higher average wage and profits in the local economy. A recent paper by Dauth, Findeisen, Moretti & Suedekum (2022) shows that higher local employment density is associated with a stronger intensity of PAM between firms and workers. In thicker labor markets, due to repeated interactions and frequent contacts, firms may have better access to information on workers and top quality firms can be more effective in attracting high quality workers, generating stronger PAM.

In this paper we analyze whether an inflow of immigrant workers affects the extent of PAM between firms and workers in a local labor market. On one hand, immigration increases the size of the local market, and through this simple "scale" effect, it may enhance the "thickness" externalities found in Dauth et al. (2022). On the other hand, and perhaps more interestingly, immigration changes the local distribution of skills. As immigrants have different backgrounds, cultures and experiences, the range of their quality (ability/productivity) is likely to be broader than for natives. Moreover, due to linguistic and cultural barriers, their productive quality may be hard for local employers to assess, especially initially. Under these conditions, when the share of immigrants in a labor market becomes larger, employers' uncertainty on the quality of workers they face may increase. As a consequence, in the presence of productive complementarity between firms' and workers' quality, better firms have stronger incentives to screen workers because their returns to a "positive match" are larger.

Hence, with an increase in the share of immigrants, high quality firms may be more likely to screen in order to attract high-quality workers, leaving low-quality workers to low-quality firms. This would be an additional unexplored channel leading to a correlation between the degree of positive assortative matching and the inflow of immigrants in local labor markets. Through this channel immigrants may have a positive “spillover" effect on average productivity, average firm's profits and wages but also on wage dispersion in a labor market.[1]

Using an employer-employee data set covering all private-sector workers in France in the years 1995-2005, this paper tests whether there is an association between immigration and positive assortative matching in local labor markets. We first calculate the average quality of each worker and firm. We then use employer-employee matches in each local labor market and year to measure the strength of PAM and its change over time. As proxy of PAM we first use the rank correlation between worker and firm quality in a district-year (as in Dauth et al. 2022). Additionally, we use the (net) share of positive assortative matches in the district-year, calculated as share of firm-worker matches where both parties are above or both below the mean quality, minus the share of mismatches (those where firms are above median quality and workers below, or vice-versa), as in Davidson, Heyman, Matusz, Sjoholm & Zhu (2012). We then analyze whether the change in immigrant share in a district over time is associated with changes in these measures of PAM. To address the endogeneity problem of immigration, we use a version of the shift-share instrument à la Card (2001). We construct it using the 1982 origin-specific share of immigrants across districts, interacted with (either *predicted* or *observed*) origin-specific flows of immigrants to other EU-15 countries (excluding France) between 1995 and 2005. Following the recent econometric literature we check the validity of this shift-share instrumental variable (IV). First, we check its correlation with pre-period economic and demographic variables. Then, we follow Goldsmith-Pinkham, Sorkin & Swift (2020), in subjecting the 1982 shares that are most relevant for identification, to tests of correlation with observable characteristics and pre-trends. Finally, we consider a plausible exogeneity test, following Conley, Hansen & Rossi (2012), that generates an estimated range of the parameter of interest under the assumption of imperfect IV and reasonable correlation between IV and the residuals. All these tests are consistent with IV validity and suggest that 2SLS estimates are robust and reasonably reliable.

Our main results show that an exogenous increase in immigrant workers as share of the population is associated with significantly stronger assortative matching between firms and workers. This result is

[1] This effect is different from other potential productivity effects analyzed in the literature, even when considering search and matching. In Chassamboulli & Palivos (2014) and Battisti, Felbermayr, Peri & Poutvaara (2018), for example, immigration attenuates the effects of search frictions in the labor market, decreasing the equilibrium unemployment, but the impact works through a job creation channel due to lower bargaining power of immigrants.

robust to different choices in the measure of assortative matching and to different proxies for firm and worker quality. The IV estimates are consistent with a causal effect of immigrant share on assortative matching. A one percentage point exogenous increase in the population share of immigrants in a district implies an increase in the share of positive assortative matches (net of mismatch) by 2.2 percentage points. This corresponds to 25% of the difference in the PAM gap between a district at the 25^{th} percentile of PAM intensity and a district like Paris, at the top 75^{th} percentile of the distribution. If the effect is mostly driven by an increase in high quality firms matching with high quality workers, as our results also suggest, this increase in the strength of PAM would correspond to 0.6 percent increase in average wages in the district. This channel therefore can generate a non trivial average wage increase driven by immigrants.

In line with the consequences of positive assortative matching with productive complementarity between workers and firms' quality, we find direct evidence of immigration increasing the average wage and particularly that of high-quality workers, increasing average firm profits and the dispersion of wages in local labor markets. The worker-firm matching highlighted in this paper provides an additional and so far unexplored mechanism that may contribute to explain the non-negative effect of immigrants on native average wages in local labor markets (Pischke & Velling 1997, Card 2005, Ottaviano & Peri 2012, Dustmann, Frattini & Preston 2013) and their positive productivity effect (Peri 2012; Mitaritonna, Orefice and Peri 2017 Beerli et al. 2021).

We then provide several pieces of evidence that are consistent with PAM taking place due to increased screening, especially by high quality firms, in sectors with more immigrants and lower screening costs. First, we show that the quality dispersion of immigrant workers is larger than that of natives; and in regions where such a quality dispersion of immigrants is higher the impact of immigration on PAM is larger. Second, as better screening is more valuable to high-quality firms because of productive complementarity, we find that high-quality workers (above the median of the quality distribution) become much more likely to transition from low- to high-quality firms when immigrants increase. Third, we show that the causal effect of higher immigrants share in the labor market on PAM intensity is stronger in industries that use initially more immigrants, and have less costly or cumbersome screening procedures: when screening costs are relatively small, large inflows of immigrants are more likely to push firms to start screening in local labor market. Fourth, we show some evidence consistent with screening costs being in large part a fixed cost for a firm, as aggregate time-cost of screening per employee do not vary much with firm size. Consistently with firms investing in better overall screening when more immigrants are available, we show that also native workers increase their degree of PAM with firms as a consequence of larger inflow of immigrants. Finally, we find that firms increase resources devoted to screening, in the form of the share of recruitment personnel, those workers involved in hiring of new workers, in response to more immigrants.

This paper contributes to two areas of research. The first is the recent literature on the local and global factors affecting matching between firms and workers. Davidson et al. (2012) show that trade liberalization improves the degree of matching for export-oriented industries. In the same vein, Davidson, Heyman, Matusz, Sjoholm & Zhu (2014) shows that export-oriented sectors display a higher correlation between firm and worker types. Bombardini, Orefice & Tito (2019) show that the workforce composition of exporting firms has higher average quality and lower dispersion of worker types than domestic firms; this is consistent with the idea that exporters have higher incentive to screen for high quality workers and select those. Focusing on local factors affecting worker-firm matching, Dauth et al. (2022) find that higher local density is associated with stronger PAM. The study argues that in thicker labor markets, high quality firms are more likely to meet and attract high quality workers.

A second related branch is the literature on the local economic consequences of migration. The channel highlighted in this paper is new in this literature and contributes a new additional explanation for the non-negative effect of migration on the average wages of native workers, a result often found in the literature (see Friedberg and Hunt 1995 and Lewis and Peri 2015 for surveys of the labor market effect of migration).[2] While many papers find small wage effects and possible positive productivity effects from immigration,[3] this is the first paper that focuses on assortative matching between firms and workers as a channel to explain a positive average wage effects of immigration. The only partial exception we are aware of is a recent theoretical contribution by Burzynski & Gola (2019) that includes a matching mechanism—not empirically tested—in a general equilibrium model with heterogeneous firms and migration. The proposed explanation related to screening as a consequence of immigration, is also, to our knowledge, new in the literature. Other explanations for our findings are possible, and we

[2] Other explanations for the small effect of migration on native wages include the productivity increases resulting from more efficient allocation of tasks between native and migrant workers (migrant and native workers' complementarity), and a boost in innovation (Peri 2012; Peri and Sparber 2009; Mitaritonna et al. 2017).

[3] Card (2005) found that immigrants had little if any effect on wages at the local labor market level. Similarly Pischke & Velling (1997) and Dustmann et al. (2013), respectively for Germany and UK, do not find any negative effect of immigration on the wages of native workers. Using French data Edo (2019) shows a null wage effect of immigration in the long-run.

consider them, but we provide suggestive evidence consistent with “screening” as a relevant channel triggered by immigration.

The rest of this paper is organized as follows. In section 2 we discuss frameworks in which immigration may affect matching, spelling out in particular the “screening” channel and the implications that this has on wages and profits. In sections 3 and 4 we discuss the data, the measures used to approximate firm and worker quality, and the strength of PAM in our sample. In section 5 we discuss the empirical strategy and some stylized facts. In sections 6 we present the estimated effect of increased immigration on assortative matching and on average wages, profits and wage dispersion. In section 7 we present additional evidence that is consistent with the effects of immigration on PAM being mediated by increased efforts in screening of workers among firms, especially those with high productivity. Section 8 concludes the paper

2 Why do immigrants affect matching?

In this section we describe some of the reasons why the inflow of immigrants in a labor market may generate higher correlation in employer-employee quality matching. We first discuss a novel channel, based on firms doing screening, and we spell out its implication on assortative matching and, in turn, on average wages, profits and on wage dispersion. We then consider additional explanations, based on ideas suggested in the literature on agglomeration economies and on the impact of immigrants.

2.1 Quality dispersion and increased screening

A reason why larger presence of immigrants could increase assortative matching is related to the fact that immigrant workers' quality is more heterogeneous than natives. This is an empirical regularity as immigrants come from different countries with different schooling institutions, and degrees of self-selection that vary by country of origin (e.g. Borjas 1987). Additionally, their quality can be harder to assess by employers because of language and cultural differences. For high quality firms, if there is productive complementarity between firm and workers' quality, a larger presence of immigrants implies stronger incentives to screen more carefully the quality of potential employees, so they can match with high quality ones. If the technology to screen workers is similar for natives and immigrants and has a significant fixed cost component of implementation (setting up a recruiting office), we would observe high quality firms paying the screening costs, apply this technology to all hires and match with high quality immigrant (and native) workers.[4] Lower quality workers would then be available for lower quality firms to hire.[5] In Appendix B we propose a simple model to illustrate such mechanism in the context of a local labor market with native and migrant workers of 2 types (high or low productivity) and firms of two types (high or low productivity). In Appendix B, we also show the conditions under which these results extend to the case with N different quality levels and with different screening costs across firms.

In line with the intuition described above, in Appendix B we also show that assortative matching (relative to random matching) generates higher average surplus in a labor market from the employer-employee match, given the complementariety (convexity) of production function in quality levels. This implies higher average profits and higher average wages (as employers and employees split the surplus), as well as higher wage dispersion.[6] As the firm's screening is hard to observe, we will not be able to test directly this model. However, we will test the impact of immigrants on the strength of PAM, average profits and wages and some additional indirect implications of the screening cost mechanism. Namely, we will test: (i) whether high-quality firms are those whose hiring of high-quality workers increases with immigration, (ii) the fact that, consistently with fixed ex-ante screening cost, PAM will increase for both native and immigrants workers, (iii) whether the share of recruitment personnel, a proxy for screening intensity in French firms, increases with immigration and (iv) whether sectors with large average employment of immigrants and with lower initial screening costs are those where the effects of immigrants on PAM are stronger.

2.2 Other channels

An additional explanation for why immigrants may affect PAM is provided by the literature on agglomeration economies. Dauth et al. (2022) show that in locations with higher employment density, the degree of positive assortative matching between firms and workers is significantly larger than in location with low employment density. Their explanation for this is that higher density of workers (thicker labor markets) for each type of skill increases the number of potential applicants and matches for each vacancy (job opening) and hence improves the quality of the worker matched to such a vacancy. Hence, high quality firms, who pay better wages, have higher probability of successfully hiring

[4]Evidence in favor of the fixed cost nature of screening is discussed in Appendix section B.

[5]We will provide some evidence consistent with screening cost having a significant fixed component in section 7 below.

[6]A similar mechanism is analyzed for the effect of trade liberalization on the intensity of assortative matching by Helpman, Itskhoki & Redding (2010) and Davidson, Matusz & Shevchenko (2008).

high quality workers. This is a simple-and-nice implication of models with frictional search, and thick market externalities (e.g. Diamond 1982 or Acemoglu 1997). In this set-up, an inflow of workers in a market, by increasing the local employment density, would contribute to higher correlation between employers' and employees' quality. As immigrants are also more likely to locate in high density cities (as shown in Peri 2016 and Albert and Monras 2018), a correlation between a larger immigrant share and stronger assortative matching may arise as a consequence of the higher employment density. We explicitly control for employment density in our estimations.

Besides making local labor markets denser and more heterogeneous in workers' quality, immigrant workers may also increase the "horizontal" differentiation of skills, filling some workers' types that natives leave sparsely populated. In other words, immigrants are not just more heterogeneous than native workers in their quality, but they are different from/complementary to them (Ottaviano & Peri 2012, Peri & Sparber 2009). They have manual, language, cognitive and communication skills that are, at least partially, horizontally differentiated from those of natives. If specific employers are looking for skills closer to their "ideal type" and immigrants make the distribution of skills broader and denser, a larger presence of immigrants can improve the match between the employer-type and the employee-type.[7] If the employer-employee production complementarity is highest when the match brings together two agents that are as close as possible, then at least for some employer and in some sectors, the presence of immigrants will increase the fit of the match and intensify the overall firm-employees complementarity.

The proposed explanations are connected to each other. Immigration makes the local labor market thicker, more heterogeneous in quality, and more diverse in skill. This increases the incentives, opportunities and the returns, especially for high quality firms, to match with the "right" high quality workers. Let us finally notice that a key component for PAM to increase average profits and wages and their dispersion in any model is production complementarity of workers' and firms' quality. The simplest form of this is complementarity (as in the model in Appendix B) is generated by a surplus that is multiplicative in those. This implies log additivity in the workers' and firms' quality and it is exactly the assumption made in the AKM method (Abowd et al. 1999), in generating the log wage regression. Hence, our empirical construction of the workers' quality indicators is consistent with what assumed in our simple model in Appendix B.

[7] Think of a restaurant looking for a Bavarian-Pastry Chef or a Musical company looking for a Latin-music guitarist.

3 Data and measures of worker and firm quality

Our empirical analysis consists of three steps developed in Sections 4, 5 and 6. First, we construct proxies capturing workers' and firms' intrinsic quality/productivity, that we assume constant over the period of analysis (1995-2005). We start by estimating them using the method pioneered by Abowd et al. (1999) and perfected by Card et al. (2013) to separate in a wage equation the individual and firm components. As these measures require strong assumptions and, particularly for firms, may not be strongly correlated with actual productivity (Eeckhout & Kircher 2011), we also use simpler measures of worker quality (lifetime wage) and firm quality (labor productivity), as suggested by Bartolucci, Devicienti & Monzón (2018).[8] In the second step, following, respectively, Dauth et al. (2022) and Davidson et al. (2012), we calculate two measures of the strength of positive assortative matching (PAM) between firms and workers in each of the 101 French Districts, and for each year between 1995 and 2005.[9] Finally, using an IV regression at the district-year level we analyze whether the population share of immigrants affects the intensity of positive matching between workers and firms. The units of analysis are French districts (*départements*), the most granular geographic level of aggregation (smaller than region) for which immigration can be measured in a consistent way over our sample period.[10]

3.1 Data

Our empirical analysis uses two main data sources: (i) matched employer-employee French data (*Déclaration Annuelle des Donnée Sociales* - DADS), and (ii) balance sheet data for the universe of French firms (FICUS/FARE).

DADS is an administrative database collected by the French Statistical Office (INSEE) containing information on the employment structure of the universe of French firms. All wage-paying legal employers located in France are mandated to report information to DADS on their workforce composition. For each worker we have information on annualized real earnings, total number of hours worked, gender, place of birth (France vs abroad), occupation (4-digit PCS-ESE classification), age, job spell, district of residence, and the industry of the employer.[11]

[8] In a robustness check we follow de Melo (2018) and use the average type of co-workers as proxy for the firm type.

[9] Because of data availability in 1982 (used to build the IV) in our empirical exercise we use only 92 districts dropping the overseas districts.

[10] Using smaller geographic areas, such as French *zone d'emploi*, would imply an imprecise allocation of immigrants over time (in particular for the construction of the IV) and therefore generate significant measurement error in the explanatory variable of interest.

[11] DADS does not provide information on the specific country of origin of foreign-born workers nor on their education

Two versions of the DADS data are used in this paper. The first, DADS *Postes*, includes the entire workforce in France, in each year, in a comprehensive cross-section and can be used to compute total employment of native and immigrant workers in each French district and year. This dataset does not, however, provide information on the worker's ID, needed to link the workers over time in a longitudinal panel, and estimate the wage decomposition as in Abowd et al. 1999 and Card et al. 2013. The second, DADS *Panel*, represents a (one in twelve) sub-sample of individuals born in October of each year, for which the worker identifier (*nninouv*) is provided, and enables us to follow individuals over time.

Using DADS *Postes* we can describe the trends and characteristics of immigrants in France, between 1995 and 2005. Table 1 shows some summary statistics relative to their share in the population, their age and skills. Two facts are most relevant for our analysis. First, in the period, 1995-2005, France experienced a significant net increase in the share of immigrant workers in the workforce from 6.2 to 9.7 percentage points. We can say that immigration contributed significantly to labor force growth in this period. Second, looking at the distribution of immigrants by working skills we observe an increase in immigrant concentration among white collars and a decline among blue collars. The table further shows how immigrants distribution changed within each group, between high and low skilled.[12] The group that grew the most, and included almost one third of all immigrants in 2005, was the one of high-skill white collars raising from 21 to 31% of the immigrant employment. While the distribution of immigrants had always been concentrated in the two "extreme" cells (high-skill white collar and low-skill blue collar) and less in the intermediate ones (high-skill blue collar and low-skill white collar), the concentration in the upper extreme grew substantially in the 1995-2005 period. We can therefore say that France, during the period of our analysis was experiencing, at least in aggregate, an increase in high skilled immigration.

– Table 1 about here –

The sample used to estimate worker and firm quality measures focuses on full-time jobs (more comparable in terms of wage) where workers hold only one job at each point in time in the private sector, in each year from 1995 to 2005. The dataset covers all private-sector firms, allowing estimation of workers' and firm effects for the whole private economy in France. As full-time jobs are comparable in terms of hours worked, our measure of wages mainly reflects differences in hourly pay across workers

levels.

[12]The Eurofond conversion table (`https://www.eurofound.europa.eu/surveys/ewcs/2005/classification`) has been used to map PCS 2-digit workers occupation codes into white-blue collar and high-low skilled worker catagories.

(see Card et al. 2013). In Table 2 we show the number of full-time workers, for each year, who can be linked over time through their ID and do not have missing information on annual wages. On average, more than one hundred and ten thousand workers per year can be tracked over time. In the data 5.1% of workers move between employers (on average) every year, as revealed by a change in employer identifier (SIREN) between time $t-1$ and t (see the fourth column of Table 2 for the number of workers that change firm by year, i.e. movers). The percent of movers is a crucial statistic in the AKM decomposition. Worker quality can be identified only if there are enough workers moving across firms and connecting them so that we can separately estimate workers' and firms' effects (see next section for detailed discussion). In DADS data (*panel* and *postes*) each firm is identified by a unique identification code (called SIREN), so DADS data can be easily merged with balance sheet data, which we use to construct characteristics of the firm, including measures of its productivity.

– Table 2 about here –

The firm identifier SIREN is assigned by the French statistical office (INSEE) for administrative purposes and may potentially combine multiple plants in France. Most firms only have one plant, and the great majority of multi-plant firms have plants in the same district, so that the location of the firm (headquarters) and of the plant(s) coincide in the overwhelming majority of cases. Only 2% of firms in our sample have plants (workers) in more than one district.[13] Notice that the firm identifier changes when a firm changes its ownership. This means that when a SIREN disappears from the dataset, it does not necessarily signify the "death" of the firm (similarly, the entry of a new SIREN does not necessarily signify the "birth" of a new firm). Considering new ownership as a new employer is, however, reasonable and commonly done (e.g. Card et al. 2013), as the new owner often introduces new managerial practices and/or technologies (Guadalupe, Kuzmina & Thomas 2012).

FICUS/FARE data report standard balance sheet information (value added, sales, total employment, capital, intermediate inputs, industry etc.) for French firms over the period 1995-2005. These data are used to compute the Value Added Per Worker – VAPW – (used as the main proxy for the quality of firms) and the Total Factor Productivity –TFP – of firms over time (used as an alternative proxy for the type of firms in appendix tables). For coherence with the DADS data, we drop firms that employ part-time workers only. We also exclude from the sample all firms with a missing SIREN code. Finally, our estimation sample includes on average almost 45,000 firms with a median size of

[13] In section 6.2 we show results excluding large firms who are likely to have plants in different districts.

approximately twenty employees (see Table 2). FICUS/FARE data are also used to compute district specific control variables, such as the average capital-labor ratio and the intermediate input intensity of firms in the district - see section 6.2. The district's export intensity, used as an additional control variable in section 6.2, has been computed by aggregating firms' exports from French Customs at the district level.

3.2 Quality of workers and firms

In order to measure firm-specific and worker-specific quality, we use two approaches. First we use simple, robust measures, but likely to include some error and based on strong assumptions. For workers, we consider the average residual lifetime wage; for firms, the value added per worker. The worker's average residual *lifetime* wage, conditional on observable characteristics, is generated by regressing individual (log) wage on age, sector, and year dummies, taking the residuals, and averaging across the years over which the individual is observed. It captures the average lifetime wage, controlling for age profile and observables, and is therefore a proxy of the average intrinsic productivity/quality of a worker over her lifetime. By controlling for sector and year fixed effects we purge aggregate trends and industry heterogeneity in wage setting. The advantage of this measure is that it is intuitive, easy to calculate, and robust. The disadvantage is that it does not "clean" for location and firm-specific effects. The same is true for the average value-added-per-worker measure for firm quality, which may include some worker-specific factors.

A more sophisticated alternative is to use the wage decomposition proposed by Abowd et al. (1999) - AKM hereafter - as well as Card et al. (2013) and Dauth et al. (2022), among others, to separate worker and firm-quality. This is done by estimating a Mincerian wage regression over the whole 1995-2005 period. We regress the (log) individual yearly wage of full-time workers on worker fixed effects (α_i), firm fixed effects ($\Phi_{\mathbf{J}(i,t)}$),[14] and a set of observable time-varying individual characteristics ($X_{i,t}$) including a quartic polynomial in age,[15] an *Ile de France* dummy,[16] and a gender dummy interacted respectively with quartic polynomial in age, *Ile de France*, and year dummies. The estimated equation is as follows:

[14]The function $J(i,t)$ gives the identity of the unique firm j employing worker i at time t.

[15]As discussed in Card, Cardoso, Heining & Kline (2018) we prefer controlling for the age rather than the experience of the workers because experience may be an endogenous outcome in the labor market.

[16]Following Abowd et al. (1999) we include an *Ile de France* dummy to control for the specificity of the Parisian labor market, identified on changes in the district of residence of the workers over time.

$$ln(wage)_{i,t} = \alpha_i + \Phi_{\mathbf{J}(i,t)} + X_{i,t} + r_{i,t} \tag{1}$$

In this specification, the worker fixed effect (α_i) can be interpreted as the time invariant component of worker's productivity, which is a proxy for the quality of a worker. The assumption is that such quality does not vary over the period considered, as it is intrinsic to worker's characteristics and that it is uncorrelated with the firm specific component ($\Phi_{\mathbf{J}(i,t)}$). Similarly, ($\Phi_{\mathbf{J}(i,t)}$) is also time-invariant, and can be interpreted as a firm-specific component of the wage. More specifically, the firm fixed effect ($\Phi_{\mathbf{J}(i,t)}$) obtained using the AKM method is a proportional wage premium paid by a specific firm j to all employees (this is the firm's component of surplus-sharing in a standard log-additive wage setting model). In a robustness check we slightly depart from the original AKM decomposition, and include the broad occupation category of workers among the set of controls $X_{i,t}$ to capture the observable, formal skills of workers. As occupational choices are endogenous to productivity this specification may be over-controlling and hence is not our main specification.[17]

The identification of worker-specific effects and firm-specific effects using the AKM method relies on workers moving across firms over the period considered, and on the assumption that any other wage component which is specific to the firm-worker match is not too relevant and/or not systematically correlated with either the firm or the worker quality. In our sample, as reported in Table 2, 5.1% of workers move across different firms annually, so that over the 10 year period more than half of workers have experienced at least two employers.[18] This significant degree of mobility reduces but does not eliminate the concern of limited mobility bias in our sample. This represents an important issue in our context because small districts may have limited workers mobility and therefore biased AKM estimates.[19] We address this concern in two ways. First, we follow a very coarse (but intuitive) approach, and drop from the AKM estimation less populated districts (below the 25^{th} percentile in the number of workers in the 1995-2005 period). Second, we estimate *group* effects rather than *firm* fixed effects in AKM estimation. Namely, we cluster firms into fifteen groups with similar wage structure using the k-means cluster analysis.[20] Given the larger mobility between cluster of firms, the limited mobility bias concern is reduced (see Dauth et al. 2022, and Bonhomme et al. 2019). Appendix C

[17] Namely we control for the high-skill occupational dummy (i.e. whether the worker is employed in skilled white- or blue-collar job). This variable is identified on workers that change occupation category over time.

[18] Assuming that one worker moves only once over the sample period.

[19] This is an additional reason for considering lifetime wage based measures as our baseline proxy for workers type.

[20] We use quartiles and deciles of firm's wage distribution to conduct the k-means cluster analysis.

shows the results obtained when taking these alternative approaches.[21]

In Appendix C we discuss and check the orthogonality conditions underlying the AKM decomposition and the estimation results. In particular, we show the symmetry in log wage losses/gains between individuals moving from firms above to firms below the median of productivity, and vice-versa (as in Card et al. 2013). This is consistent with log additivity of quality of workers' and quality of firms and random match-specific residual, in generating the log wage of an employee. In Appendix C we also show that a fully saturated model with job-specific fixed effects yields only a slight improvement in the fit of the data relative to the model we estimate (including only firm and individual effects), as suggested by the very small increase in the R-squared from 0.952 to 0.954 when saturating with employer-employee fixed effects. This suggests that match-specific effects are not very relevant in explaining log-wage variation across employer-employee matches, once the individual and firm components are accounted for. Finally, in Table C2 we show descriptive statistics of the parameters obtained from the estimation of equation (1). Notice that the AKM parameters obtained using French data are qualitatively similar to those obtained by Dauth et al. (2022) and Card et al. (2013) on German data. Namely, we obtain similar mean (and median) worker effects as in Dauth et al. (2022). Also, we obtain a correlation between worker and firm fixed effects which is small and in line with Dauth et al. (2022) when they use the 1985-1991 period. In line with both Dauth et al. (2022) and Card et al. (2013) we obtain that the standard deviation of worker effects is larger than that of firm effects.

Firm fixed effects from the AKM decomposition, while often-used, represent the employer-specific component in wage setting (see Abowd et al. 1999; and Card et al. 2013),[22] and they are likely a imprecise measure of productivity/quality of firms, as it is not always true that firms with higher productivity level pay higher wages. A recent strand of the literature suggests that when wages are non-monotonic in firm type, then firm fixed effects in AKM decomposition are only weakly correlated with firm productivity (Gautier & Teulings 2006, Eeckhout & Kircher 2011, de Melo 2018). Hence, in the same vein as Bartolucci et al. (2018), we adopt as baseline measure of firm quality (productivity), its Value Added per Worker, VAPW. In robustness checks in Table A4 we provide baseline results

[21] A third way of addressing the limited mobility bias would be applying the leave-out estimation proposed by Kline, Saggio & Sølvsten (2020). Two reasons prevent us to adopt this methodology. First, the procedure is very demanding in terms of RAM memory and cannot be implemented in our 8Gb RAM server (where confidential DADS data are stored). Second, the procedure has to be applied district-by-district. Hence, fixed effects are identified only within-district mobility, and therefore hardly comparable across districts.

[22] Many papers analyzing the role of the workplace component in rising wage inequality have used firm fixed effects from AKM decomposition as a measure of the surplus obtained by all employees in a given firm (i.e. employer-share of the surplus in a wage setting environment). See Abowd et al. (1999); and Card et al. (2013).

using firm fixed effects from the AKM decomposition as a proxy for the type of the firm. As a further robustness check, in appendix Table A4 we follow de Melo (2018) and use the average co-worker type as a proxy for firm type. In the de Melo (2018) approach, the strength of positive assortative matching is approximated by the correlation between worker type and the average type of his/her coworkers. Finally, in Table A4 we also report a robustness check using TFP (rather than value added per worker) as a proxy for the type of firm.[23]

4 Measuring within-district assortative matching

A first measure of the intensity of assortative matching in a district (following Davidson et al. 2012) is represented by the difference between the share of positive assortative matches and the share of mismatches in each district. The share of positive assortative matches is the sum of the share of high-quality workers employed in highly-productive firms (π_{HH}) and the share of low-quality workers employed in low-productivity firms (π_{LL}), where high (low) quality workers/firms are those above (below) the median of worker/firm distribution (in each district). By contrast, the share of mismatch involves the share of high-quality workers in low-productivity firms (π_{HL}) and the share of low-quality workers in highly-productive firms (π_{LH}). Hence, this indicator for district d at time t is equal to $(\pi_{HH}+\pi_{LL})-(\pi_{HL}+\pi_{LH})$. The second measure of intensity of assortative matching, following Dauth et al. (2022), is the rank correlation between workers and firms types. Based on their type, we rank workers and firms within each district and compute the rank correlation between firm- and worker-types for each local labor market and year.[24] In the next sections we show descriptive evidence on the intensity of assortative matching, on average productivity and on the immigrant share across French districts.

4.1 Stylized facts on within-district matching

Before moving to the formal econometric analysis, we characterize some important empirical facts on the existence of positive assortative matching and its correlation with presence of immigrant workers and with average productivity in the district.

[23] The TFP of firms has been calculated using the Wooldridge (2009) approach.

[24] In the baseline specification we set to 0 correlation which are not significant at the 10% level. In several checks we include all correlation values as they are (abstracting from statistical significance). We also use Pearson correlation values as a robustness check.

4.1.1 Worker-Firm matching in the aggregate economy

Figure 1 plots the empirical distribution of workers types (measured as lifetime residual wage) separately for individuals employed by high- and low- productivity firms as measured by Value Added per Worker. Highly productive firms—defined as those having Value Added per Worker above the 75^{th} percentile of the distribution– indicated with a solid line in Figure 1 employ (on average) higher quality workers relative to low-productivity firms—defined as those with value added per worker below the 25th percentile– represented by dashed line. This figure indicates higher average quality of workers in higher average quality of firms but also shows a large share of worker-firm "mismatches" as the distribution of workers in high quality firms extends to low quality levels.[25]

– Figure 1 about here –

In Table 3 we report the share of positive assortative matches (π_{HH}, π_{LL}) and mismatches (π_{LH}, π_{HL}), in 1995 and 2005 in aggregate. We use Value Added per Worker as proxy for the firm type, and lifetime conditional wage as a proxy for worker type. The table clearly shows that the share of positive assortative matching (around 60%) is larger than the share of mismatched firms (about 40%). Nevertheless, the presence of a significant share of mismatch is consistent with the idea that there could be information asymmetries, searching costs and other frictions limiting the ability of high quality firms to match with their preferred (high quality) workers. The numbers shown in Table 3 are similar to those obtained by Davidson et al. (2012) on Swedish data. About 60% of the firm-worker matches are assortative, and about 40% are mismatched.

– Table 3 about here –

4.1.2 Worker-quality distribution and immigrant-intensity

One reason described in section 2 for immigration to increase positive assortative matching is the larger quality dispersion of immigrant workers. In this section we show evidence that the empirical distribution of migrant workers' quality is indeed more dispersed than that of natives.

First, in Table 4 we show that the average quality of native workers—as captured by average lifetime wage—is only slightly larger than that of immigrants. At the same time, the standard deviation and

[25] Defining firm productivity according to the firm-effect in AKM, shows much smaller average difference in the quality of workers for high and low quality firms.

the interquartile range of worker quality are about 10 percent larger for immigrant than for native workers, whether we use residual lifetime wage or AKM worker fixed effects as a proxy for worker quality. Also, the top-1 percentile in the workers' ability distribution (especially when measured as lifetime conditional wage) is higher for immigrant than for native workers (while the bottom 1% is lower for immigrants than for natives), suggesting that the incentive of high quality firms to match with top workers is likely higher when immigrants are in the labor force. A Kolmogorov-Smirnov formal test of equal distribution of quality between natives and immigrants reject such hypothesis at the standard confidence level.

– Table 4 about here –

Additionally, we show that across districts and over time the immigrant share is associated with higher dispersion in worker quality. In Table 5 we regress, separately, the 5^{th}, 10^{th}, 25^{th}, 75^{th}, 90^{th} and 95^{th} percentile of the workers' quality distribution in the district-year, on the corresponding share of immigrants. Controlling for region-by-year fixed effects and district-specific control variables (including the average worker type in the district), Table 5 shows negative coefficients for percentiles of the wage distribution below the median, and positive coefficients for percentiles above the median. This is consistent with the presence of immigrants in a district being associated with a more dispersed distribution of worker quality: negative correlation with low-percentile types and positive correlation for high-percentile types. In Table A1 of the Appendix, we estimate the same regression using different measures of workers' quality dispersion, such as the standard deviation, the interquartile range, and the max-min difference in worker types, for each district. Conditional on region-by-year fixed effects and district-specific controls, districts with high shares of immigrants show a larger dispersion of worker quality as suggested by the positive coefficient for the standard deviation, and the interquartile and min-max ranges.[26]

– Table 5 about here –

[26] Regressions reported in Table 5 and Appendix Table A1 include district-specific controls (population, share of skilled workers, and concentration index of firms in the district) to be consistent with the econometric estimations reported in section 5.

4.1.3 Positive matching and districts' productivity

If stronger assortative matching leads to an improvement in the allocation of labor within French districts, then it should be associated with a higher level of average labor productivity. This is shown in Table 6 where we report the correlation between the strength of assortative matching and the average value added per worker in the district. Controlling for district and region-by-year fixed effects, we find that the degree of assortative matching (as revealed by the rank correlation between firm and worker type) is significantly and positively correlated with the average labor productivity of the district. Similar results are obtained if we measure the strength of matching as the share of positive assortative matching minus the share of mismatch. Table 6 also shows that the association is similar whether we use AKM fixed effects or average residual lifetime wage as the measure of worker quality.[27]

– Table 6 about here –

4.1.4 Immigration and matching: a first glance at data

Figure 2 shows the raw correlation between immigration and matching across French districts. On the vertical axis we plot the change between 1995 and 2005 in the degree of assortative matching in each district as revealed by worker-firm quality rank correlation (panel a) and strength of positive assortative matching (panel b). We use the lifetime wage as proxy for worker type and the value added per worker as a proxy for firm quality. On the horizontal axis we plot the change in the population share of immigrants over the period 1995-2005. By taking long-run differences, district specific (time invariant) factors are controlled for. All the scatter plots reported in Figure 2 show a positive (albeit weak) correlation between increase in immigrants and change in the strength of positive assortative matching. These correlations are consistent with more immigration being associated with stronger PAM.

[27] To check that our data match the findings obtained in previous literature we also show, in Appendix Figure A1, that the correlation between population density and positive assortative matching across districts is positive and significant. Dauth et al. (2022), show such correlation in German regions, and they suggest that denser districts have stronger positive worker-firm type correlations as a consequence of stronger assortative matching in denser and thicker labor markets.

5 Immigration and firm-worker matching at the district level

In this section we discuss more formally the empirical approach and the identification strategy based on an Instrumental Variable approach.

5.1 Empirical model

Our basic empirical specification is as follows:

$$y_{d,t} = \beta_1 \mathit{Immi\ Sh}_{d,t} + \beta_2 X_{d,t} + \theta_d + \theta_{rt} + \epsilon_{d,t} \tag{2}$$

where the subscript d and t stand respectively for district and year; θ_d and θ_{rt} are district and region-by-year fixed effects (there are 23 regions in France and each of them includes on average 4 districts).[28] District fixed effects control for unobservable time invariant factors, such as geography, municipal institutions, market potential that may affect the firm-worker match. Region-by-year fixed effects are then included to control for any region-specific time changes driven by local economic and demographic changes and changes of labor laws, business regulations and other policies, usually issued by regional governments. The set of control variables $X_{d,t}$ is parsimonious. It includes those factors that the literature has indicated as potentially affecting the matching of firms and workers. First, we include the concentration index of firms in the district, i.e. the Herfindahl-Hirschmann index of firms' market share,[29] as it is correlated with the presence of large high quality firms which could attract very high quality workers. Second, we include the (log) population of native workers in the district, which determines density and strength of agglomeration economies. Using German data, Dauth et al. (2022) show that in big cities and/or in more dense local labor markets the strength of assortative matching may be stronger. Last, we include the share of skilled workers in the district, as skill biased technical change can increase the degree of positive assortative matching (see Acemoglu 1999 and Albrecht and Vroman 2002), and the intensity of such change is associated with the presence of skilled workers. Controlling for simultaneous regressors could be inappropriate as those variables are potentially endogenous to the inflow of immigrants. Hence, we check the robustness of the coefficient of $\mathit{Immi\ Sh}_{d,t}$ to the exclusion

[28] We follow the official classification of French regions during the period 1995-2005.

[29] The Herfindahl-Hirschmann for firm concentration has been calculated as $HH_{d,t} = \sum_{i=1}^{I} s_{it}^2$, where s_{it} is the market share of firm i in its district d at time t.

of these control variables $X_{d,t}$. Table A5 shows that our results are not affected by the exclusion of controls $X_{d,t}$.

The main explanatory variable is the share of immigrants in the adult population in each district-year. In order to test the main implications described in section 2, the dependent variable $y_{d,t}$ is alternatively: (i) the rank correlation between firm and worker type; and (ii) the strength of positive assortative matching defined as in section 4. Additional outcomes considered are firms' average profit, average wages and measures of wage dispersion in the district d and year t. Firm profits are calculated as total revenues minus total costs (wage bill, purchase of intermediate inputs and raw materials) for the firm.[30] Since we do not have complete information on costs, significantly energy costs are not included, the measure of firms' profit may suffer of measurement error that systematically overstate the profits. We should keep this in mind when we discuss those results. The average wage is calculated as the district-level average of workers' yearly wage. District wage dispersion is approximated by the difference between the average wage of high- and low-quality workers.

5.2 Identification and IV strategy

As the change in immigrant share across districts over time is likely correlated with several omitted economic variables, Ordinary Least Square estimates will not identify the causal effect of immigration on assortative matching. The inclusion of a rich set of (district and region-by-year) fixed effects absorbs some of these unobservables and should reduce omitted variable bias. Nevertheless, unobserved district-year specific economic conditions may be correlated with the inflow of immigrants and with the matching process. For instance, favourable economic conditions may attract immigrants, and could be also associated to higher/lower correlation of worker-firm quality as high quality firms may become more/less "picky" in times of economic expansion. To address this issue we rely on an Instrumental Variable (IV) shift-share approach (as in Card 2001 and used in many subsequent studies). Aware of the criticism of this strategy (see Jaeger, Ruist and Sthuler 2018)[31] we follow the strategy of performing a set of checks on our IV as proposed by Goldsmith-Pinkham, Sorkin and Swift (2020). These are found

[30] We aggregate firms' profit at the level of district by a weighted average with weights equal to the size of the each firm (i.e. the share of firm's sales over total sales in the district).

[31] Specifically, Jaeger et al. (2018) argue that due to high correlation of immigrants settlements over time and to the slow adjustments of labor markets, the shift-share instrumented variable captures a combination of the short the long run (*feedback*) effect of migration. To avoid this problem, Jaeger et al. (2018) propose including in the regression the lagged instrumented migration shock to control for the feedback effect. While this argument is specific to the wage effect of immigrants, to control for the slow adjustment of our dependent variable, in Table A6 we include district specific trends and results remain qualitatively the same.

in section 5.2.1 and in the Appendix D.

The shift-share IV is constructed by allocating the aggregate inflows of immigrants to France from a given origin o, predicted as we describe below, $\widehat{Immi}_{FRA,o,t}$, proportionally to the spatial distribution of immigrants from that origin across French districts in 1982 (calculated from Labor Force Survey data, LFS):

$$\widehat{IMMI}_{d,t} = \sum_{o} \frac{IMMI_{d,o,1982}}{IMMI_{FRA,o,1982}} * \widehat{Immi}_{FRA,o,t}. \tag{3}$$

While a substantial part of the identification derives from the variation in the "share" component of the IV (Goldsmith-Pinkham et al. 2020), to reduce the probability that the "shift" component of our instrument is correlated with district-specific residuals, in the main specification we use the ***predicted*** number of immigrants to France from country o in year t based on the origin-specific flows of immigrants to other EU-15 countries (excluding France).[32] We approximate the push-driven component of migration from each origin country o by regressing the total (log) flows of migrants in France from each origin o at time t - $Immi_{FRA,o,t}$ - on the (log) flow of migrants from o to all other EU-15 countries ($Immi_{EU15,o,t}$), controlling for origin and year fixed effects:[33]

$$Immi_{FRA,o,t} = \beta_1 \text{Immi}_{EU15,o,t} + \theta_o + \theta_t + \epsilon_{o,t} \tag{4}$$

The predicted values from regression (4), $\widehat{Immi}_{FRA,o,t}$, net of the origin and year fixed effects,[34] represent the origin-year ***predicted*** inflows of immigrants in France, based on the variation of immigrant flows to other (similar) countries. $\widehat{Immi}_{FRA,o,t}$ is then used in equation (3). In two robustness checks reported in Table 10, as a shift-component of the IV in eq. (3) we use the ***observed*** immigrant flows towards EU-15 countries (excluded France), $Immi_{EU,o,t}$; and the actual aggregate immigration flows to France from each origin, $Immi_{FRA,o,t}$ (as in the traditional shift-share approach).

The spatial distribution of immigrant shares in 1982 pre-dates the creation of a common EU labor

[32]This approach is broadly inspired by the trade shift-share used in Autor, Dorn & Hanson (2013). A similar approach in the immigration literature has been used also by Bianchi, Buonanno & Pinotti (2012), whose shift-share is bases on supply-push factors calculated on bilateral migration flows toward destination countries other than Italy.

[33]Data on bilateral migration flows used in estimating equation (4) are from OECD IMD dataset. For coherence with LFS data the OECD IMD data have been aggregated by the same set of origins (or group of origins) used in the LFS data.

[34]The predicted inflows of immigrants are $\widehat{Immi}_{FRA,o,t} = \widehat{\beta_1} Immi_{EU,o,t}$. From the fit of equation 4 we subtract the year fixed effects component because it may capture French specific shocks, common across districts. We also remove the origin fixed effects component to avoid time-invariant, origin-specific patterns of migration affecting the IV.

market (1992) and hence pre-dates by more than a decade the large flow of EU immigrants in France. Moreover, the 1982 economic conditions are relative to more than a decade prior to the beginning of the considered period. This reduces the correlation between the initial distribution of immigrants and recent economic trends in the district (we test the orthogonality of the spatial distribution of immigrants in 1982 in the next section).

Finally, we calculate the imputed share of immigrants in each (district) as follows:

$$\widehat{s_{d,t}^{IMMI}} = \frac{\widehat{IMMI}_{d,t}}{\widehat{IMMI}_{d,t} + Natives_{d,1982}} \tag{5}$$

In expression (5) the native population is fixed at year 1982 so as to avoid spurious effects due to the potentially endogenous changes in the native population in the district over the 1995-2005 period.

5.2.1 Tests of validity of IV

First, we test whether the short and long-run pre-1995 trends in labor market outcomes across districts are correlated with our IV. Table 7 presents the coefficients obtained by regressing the short-run changes in employment and average wage over the period 1994-1995 (see columns 1-2), as well as their long-run changes over two consecutive LFS censuses (1982-1990), on the IV (predicted inflow of immigrants for the period 1995-2005). If pre-existing (short- or long-run) trends in employment and wages are predicted by the variation of our IV, this would suggest the existence of persistent economic conditions affecting the IV variation. None of these correlations is statistically significant, suggesting that districts that received large inflows of immigrants in 1995-2005, as predicted by the shift-share IV, did not perform differently in the pre-1995 period relative to those with fewer predicted immigrants. In Table A2 we also show the absence of correlation between the initial strength of assortative matching and the 1995-2005 change in the IV.

Second, we follow Goldsmith-Pinkham et al. (2020) in testing a crucial assumption for the validity of the shift-share instrument, namely the exogeneity of the initial origin-specific migration shares with large Rotemberg weights, i.e. those shares whose variation drives most the identification in the 2SLS average estimator. The top-5 origin-specific shares are: Ex-Yugoslavia, Portugal, Algeria, Other African Countries and Other Countries (including South America and Asian countries).[35] For this sub-sample of origins we test the correlation between the initial shares of immigrants and: (i) the

[35] The aggregation of origins adopted here is that of the original LFS data used to build the IV.

economic performance of districts in 1982 (see Table D2); and (ii) the level of strength of PAM in 1995 (see Table D3). These tests show no significant correlation and hence they support the assumption of exogeneity of the initial share of immigrants relative to pre-existing economic condition and initial PAM intensity.[36] Appendix D shows results and a detailed discussion of such validity tests.

As a third validity test, we consider the possibility that violations of the exclusion restriction can still exist and we quantify how large they can be and how they may affect our estimates. Specifically, we apply the Plausible Exogeneity test proposed by Conley et al. (2012). The test allows for possible deviations from exact validity of the exclusion restriction (i.e. non-zero correlation between the instrument and the error term in eq. 2) and checks how robust the estimate of the coefficient of interest ($Immi\ Sh_{d,t}$) is to a range of possible deviations. We therefore relax the exclusion restriction of our IV and assume a non-zero correlation between the instrument and the error term in equation (2), i.e. $\gamma \neq 0$.[37] An approximation of how far such a correlation is from the exclusion-restriction validity (i.e. $\gamma = 0$) can be obtained as discussed in van Kippersluis & Rietveld (2018). We start by identifying the sub-groups of districts for which our IV ($\widehat{s_{d,t}^{IMMI}}$) does not predict the endogenous variable ($Immi\ Sh_{d,t}$).[38] This sub-group of districts represents the ideal set to test the exclusion restriction: if the correlation between the IV and the endogenous variable is zero, then the reduced form effect of the IV on the main outcome variables (i.e. PAM measures) should be zero too. We therefore regress our four PAM measures on the imputed share of immigrants ($\widehat{s_{d,t}^{IMMI}}$) for this sub-group of districts. By doing so we have a first qualitative check of the validity of the exclusion restriction. The estimated coefficients on $\widehat{s_{d,t}^{IMMI}}$ are reported in Table A9. Reassuringly, for three out of four PAM measures, the coefficients on $\widehat{s_{d,t}^{IMMI}}$ are rather small and not statistically different from zero, suggesting the validity of the exclusion restriction.

These coefficients associated to $\widehat{s_{d,t}^{IMMI}}$ are also plausible values for γ to be used in the Plausible Exogeneity test proposed by Conley et al. (2012). Hence, we follow Conley et al. (2012) and estimate the union-of-confidence intervals by assuming γ obtained as discussed above (we used the point estimate of γ when not statistically significant). In Table A9 we report the 90% confidential intervals produced

[36] Only the share of Portuguese immigrants in 1982 is correlated with the average district wage. However, Portugal accounts for barely 4.8% of the overall 2SLS estimates.

[37] See Conley et al. (2012) section 4.

[38] Given the inclusion of district fixed effects in regressions, such a zero-first-stage regressions have been implemented region by region (with a region containing on average four districts). Therefore, the sub-group of districts for which the IV does not predict the endogenous share of immigrants is composed by the districts whose region regression produces non-significant coefficient on the IV.

using the Conley et al. (2012) test for the plausible range of γ. Only one of the 90% confidence intervals for β_1 resulting from plausible exogeneity regressions contains zero (marginally). This implies that the positive and significant effect of immigrants on the four measures of assortative matching, as revealed by our main IV estimations, is strongly robust to plausible deviations from the exclusion restriction.

Overall, the validity tests suggest that the shift-share IV, and its most relevant share components, are not correlated with pre-1995 trends nor with 1995 levels in labor market and economic conditions, and that deviations from the exact identification conditions are likely small and would not change the sign and significance of the key estimated coefficients.

6 Main empirical results

6.1 PAM and firm profits

We start by showing in Table 8 the OLS estimations of equation (2) using value added per worker as a proxy for firm quality.[39] In column 1 and 3 we find a positive and significant correlation between immigration and the measure of strength of PAM when residual lifetime wage is used as a proxy for worker type (columns 1 and 3 in Table 8). Specifications using AKM individual effects as a proxy for worker types do not show significant results.

– Table 8 about here –

Ordinary Least Squares estimates, however, may be significantly biased. Unobserved local economic conditions may produce positive or negative bias, depending on whether economic expansion/recessions generate a stronger or weaker assortative matching between firm and worker. In particular, temporary unobserved positive economic shocks may attract immigrants and reduce/increase the extent of PAM because high-quality firms find it less/more urgent selecting their ideal worker type. As we do not know much about this correlation, it is hard to give a sign to the bias. More credible are estimates in Table 9 showing the main empirical specification estimated using 2SLS in order to address endogeneity and omitted variable concerns.[40] The 2SLS estimates show a positive and significant effect of immigration, instrumented by the shift-share IV, using different measures of workers' quality and different indicators

[39] OLS regressions are weighted by the number of firms in the district. This controls for the accuracy of PAM measures, higher when more firms are available for worker-firm matches.

[40] In Table A3 we show 2SLS regression weighted by the number of firms in the district. Results are almost identical, so in the rest of the paper we rely on non weighted 2SLS regressions.

of PAM. A comparison between the OLS and 2SLS results shows an attenuation bias in the OLS estimations. The effect of immigrant share is positive, significant and similar in magnitude when assortative matching is measured by the rank correlation between firm- and worker-type (see Table 9 columns 1 and 2) as well as when it is measured by the share of positive matching net of mismatches (columns 3 and 4). In line with an additional implication of the framework in section 2, migration affects positively and significantly the average profits of firms in the district (column 5).

The coefficients of the control variables in Table 9 reveal a positive, often significant, correlation between skill intensity and firm concentration on the strength of positive assortative matching in the district. Highly concentrated districts (where few big firms dominate the local labor market and are likely to be matched with high-quality workers) show stronger positive assortative matching. Also, consistent with Acemoglu (1999) and Albrecht & Vroman (2002), a large share of skilled workers is associated with stronger positive assortative matching. Conversely, we do not find a significant coefficient of native employment. This is different from the evidence presented in Dauth et al. (2022). While our identification is in changes, Dauth et al. (2022) identify the association between density and PAM *in levels* (cross-section). In Figure A1 we show that, as in Dauth et al. (2022), there exists a positive correlation between total employment and the strength of PAM across French districts.

– Table 9 about here –

In terms of magnitude, these baseline estimates in Table 9 imply that a one percentage point (p.p.) increase in the district share of immigrants is associated with a 2.2 to 2.9 p.p. increase in the (net) share of positively assortatively matched workers in the district (see column 3-4 in Table 9). This corresponds to the 25%-35% of the gap in PAM intensity between a district belonging to the lowest quartile of the distribution (i.e. 25^{th} percentile) and one in the top quartile, like the Paris district (Île de France).[41] In other words, for a district belonging to the *median* of the distribution in the (net) share of positive assortative matches, 2.2 p.p. corresponds to an increase in the strength of PAM equal to half of the gap with the Paris labor market.

[41] The 25^{th} percentile in the distribution of the (net) share of positively sorted matches is 11.4%; the median is 15.9%. The observed value for Île de France (in the top quartile) is a net share of 20.2% in 2005.

6.2 Robustness checks

The results shown above are robust to alternative ways of constructing the instrumental variables. Table 10 Panel (a) reports results using the more standard shift-share instruments described in section 5.2 where the shift component is simply total migration to France by country of origin, as well as an alternative shift-share in which the shift component is the observed, rather than estimated, flow of immigrant to EU-15 countries excluding France (panel b of Table 10). In most cases, in line with results in Table 9, the coefficient of interest is significant, positive and between a value of 2 and 3.

– Table 10 about here –

Previous papers have identified a positive impact of international competition—measured as export intensity—on the correlation of worker-firm quality at the industry level (see Davidson et al. 2012; Davidson et al. 2014; Bombardini et al. 2019). Additionally, Acemoglu (1999) and Albrecht & Vroman (2002) show that skill-biased technical change may increase the incentives for positive assortative matching in local labor markets by increasing the gap between high- and low-skilled workers' productivity. To address whether these factors may affect the correlation between PAM and immigration, in Table 11 we control for the export intensity of the district (the log of total district exports),[42] the average capital-equipment intensity[43] and the average value of intermediate inputs relative to total production.[44] These last two variables are often used as proxies for the technological complexity of production in a district. Results in Table 11 show that the coefficient of the immigrant share is robust to the inclusion of these additional control variables. All the estimated coefficients on the share of immigrants are positive and significant and quantitatively similar to those in the basic specification. The effect on profits is even somewhat larger than in the basic specification: a 1 pp difference in the share of immigrants implies a 21% increase in profits relative to the average. This is a large effect, not very precisely estimated, relative to a baseline estimate of 14% increase for each 1 pp increase of immigrants. We should keep in mind, as discussed in section 5.1, that firm profits are imprecisely measured due to lack of information on all of firm's costs and these results must be taken with caution.

– Table 11 about here –

[42] French Customs data are used to compute the total exports of firms located in a given district.

[43] Based on FICUS/FARE data we compute the ratio between physical capital and total employment in each firm, and then take the average across firms within a district.

[44] As a proxy for the intermediate input intensity we use the ratio of intermediate input purchases and the total value of production of the firm.

In Table A4 of the Appendix A we measure the quality of firms and workers using alternative indicators. First, we use coworkers' average quality (as suggested by de Melo 2018) and firm-level TFP as measures of the quality of a firm. In both cases, we still find support for a positive effect of migrant share on the strength of PAM (in particular when the worker type is approximated by lifetime wage). Second, we use the firm-specific component of the AKM decomposition as an alternative proxy for firm quality (as in Card, Cardoso, Heining and Kline 2018). As productivity changes are usually translated into workers' wage changes, the pay premium of firms (firm fixed effects in AKM decomposition) are proxies for productivity measures. The results reported in appendix Table A4 show evidence, although not as strong, of the positive matching effect of migration. The weaker results are consistent with a small rent-sharing elasticity to productivity, so that the pay premium at the firm level is only weakly correlated with productivity measures of the firm. Finally, we measure the quality of workers after controlling also for their macro-occupation. In particular, the proxy for workers' quality (both lifetime wage and AKM fixed effects) has been measured after controlling additionally for a high skill occupational dummy. Our baseline results hold, showing still a positive coefficient on migration.

The robustness of the coefficient of interest to the inclusion of controls implies a weak partial correlations between the control variables and the share of immigrants. Nevertheless one can be worried by the inclusion of (potentially) endogenous controls in biasing the coefficient of interest. Hence we additionally run the basic regressions omitting all controls, except for fixed effects (Appendix Table A5). We find estimated coefficients very similar to those in the basic specification. Slow and persistent trends in the economic variables or in the immigrant flows may affect our results. Hence we estimate a specification adding a district-specific trend (Appendix Table A6) and the coefficients of interest barely changes.

We perform a final set of robustness checks to test the impact of outliers and weighting. First, we trim from our sample the largest and smallest firms which may have a disproportionate effect in influencing measures of assortative matching. We exclude firms of size (number of employees) below the 5th and above the 95th percentiles. Results (in Appendix Table A7) show that the coefficients of interest become slightly larger and more significant. Trimming large firms also represents a way of eliminating multi-districts firms in our sample (about 2% of them, all in the top percentiles of employment), which could generate measurement error in attributing a firm to a district. In a similar vein, we estimate a regression where each district is weighted by the number of firms (Appendix Table

A3). The goal is to reduce measurement error introduced by small districts having few firms, and therefore imprecise measures of PAM. The results are very similar to the basic specification. Finally, in Appendix Table A8, rather than setting to zero the non-statistically significant rank correlation coefficients, we include significant and non-significant estimates in the measure of the rank correlation index (in columns (1) and (2)). We also report results using the Pearson correlation index (in columns (3) and (4)). The magnitudes and significance of the effects in both cases is very similar to the baseline specification.

6.3 Industry-District as local labor market

In the analysis so far we have measured assortative matching considering all workers and all firms in each district, implicitly assuming an aggregate matching market in the district. Here we re-do the analysis, considering a district-sector as a matching markets. Moretti (2004) shows that occupation-local units are better proxies for local labor markets. Segmentation across sectors in the matching process, and differential sector-specific intensity of assortative matching could affect the aggregate results. Hence, we compute the PAM measures at district-sector level, and perform the estimates controlling for sector-year fixed effects. Results are reported in panel (a) of Table 12 and show the robustness of our baseline findings. While the IV still varies at the district-year level only, the regression cells are district-sector-year and the results show that within district-sector PAM increased, as a consequence of immigrants, once we control for any technological or demand change specific to the sector-year.

The introduction of the sector-district specific PAM measures allows also to check if the heterogeneity of effects across sectors is consistent with immigrants generating the PAM effect. In panel (b) of Table 12 we interact the share of immigrants in the district with a measure of immigrant employment intensity for the sector (i.e. share of immigrant workers in the sector in 1995). In line with intuition, the assortative matching effect of immigration is significantly stronger in immigrant intensive sectors.

6.4 Average wages and wage dispersion

An additional important consequence of PAM, in presence of production complementarity between workers' and firm's quality, is its positive association with average wages and wage dispersion. Consistently with this prediction, column (1) of Table 13 shows that the immigrant share has a positive impact on the average wages of district. This is the consequence of a negative but not statistically significant impact on low-quality workers' wages (column 3), and of a positive and significant impact on high quality worker's wages (column 2). These estimates, reminiscent of what found in other studies (such as Dustmann et al. (2013)), are consistent with immigration increasing positive assortative matching. To show even more clearly the impact of immigrant share on wage dispersion, columns (4) and (5) show the 2SLS regression results on the difference in the (log) average wage between high- and low-type workers—respectively, workers with quality above and below the median—in each district-year.[45] This measure of dispersion is similar to the 75-25 log wage percentile difference in a district. The results suggest that an increase in the share of immigrants by one percent of population is associated with a significant increase in the wage inequality in the district by about 1.3 percent, mostly due to an increase in the wage of high quality workers.[46]

We can also check how much of the estimated effect on high quality worker's wage increase (driving the increase in inequality) can derive directly from the magnitude of the estimated PAM effect. To do that, we first use the dual measure of positive assortative matching and we multiply the share of high quality workers who moved to high quality firms in response to a one percent increase in immigrants (which is equal to the estimated effect of 2.9 percent divided by the share of high quality workers, i.e. 50%, generating a 5.8 percent of that population upgrading their wages) times the increase in wage as percent (log wage) associated to the transition of high quality workers from low to high quality firms (as estimated in figure C.1) equal to about 11 percent. This gives a change of 0.64 percent, which is about half of the estimated effect in Table 13. Hence, the PAM channel accounts for about half of this estimated impact on wage inequality.

– Table 13 about here –

7 Additional evidence consistent with the screening mechanism

In this section we show interesting additional results, that, taken together, are consistent with the explanation – discussed in section 2 – that higher immigration may encourage screening, especially by high quality firm, generating increased PAM. While we are not ruling out a role for pure thickness effects and other forms of complementarity between immigrants and firm quality, we emphasize screening and

[45] The worker type is approximated by lifetime wage in columns 4 and AKM fixed-effect decomposition in column 5.

[46] All specifications include district fixed effects, region-year fixed effects and all the district-specific controls discussed above (both baseline and additional controls).

its implications as consistent with these findings.

7.1 Heterogeneous effect based on immigrant quality dispersion

An interesting corollary of the "screening" mechanism presented in section 2 and formalized in Appendix B is that the probability of positive assortative matching is larger when the standard deviation of immigrant quality is larger (i.e. when the uncertainty on immigrant workers type is larger). See *Corollary 1.1* in Appendix B. We test this by interacting the share of immigrants in the district with two bins constructed from percentiles of immigrant-quality dispersion across districts at the beginning of the period—*binned model*. We therefore extend the empirical equation (2) as follows:

$$y_{d,t} = \sum_k \left(\beta_k \mathit{Immi\ Sh}_{d,t} * \mathit{Dispersion\ Bin}^k_{d,t0}\right) + \beta_2 X_{d,t} + \theta_d + \theta_{rt} + \epsilon_{d,t} \quad (6)$$

where variables and subscripts are the same as in the previous sections, k denote the bins adopted to explore the heterogeneous effect of migration on the strength of assortative matching $y_{d,t}$, and $Dispersion\ Bin^k_{d,t0}$ identifies whether the specific district d belongs to a specific bin k at t_0 (1995). Based on the distribution of immigrant types in 1995 in each French district, we define: (i) bins for districts having an inter-quartile range of immigrant types above/below the median; and (ii) bins based on min-max difference in immigrant types in the district.[47] We instrument each interaction between $Immi\ Sh$ and the dispersion bin with the interaction between the instrument $\widehat{s^{IMMI}_{d,t}}$ and the dispersion bin. Results are reported in Table 14. We find that immigrant share has a positive, significant and (slightly) stronger effect on the intensity of assortative matching in districts with a dispersion of immigrant types above the median (in 1995). Results are stronger when using dispersion bins based on min-max difference in immigrant types as measure of dispersion (see columns 2, 4, 6 and 8 in Table 14). In this case the PAM effect of immigration is mainly driven by districts with higher initial dispersion in immigrant-types. Using the inter-quartile range the difference between the two coefficients is usually in the direction of larger value for the bin with larger initial dispersion, but the difference is not significant. While rather noisy (F-stat of a test of equal coefficients is below 10) these results are suggestive that larger dispersion of immigrant quality, pushing firms to screen for the "good" worker, is associated with stronger assortative matching.

[47] We take these proxies in the initial year (1995) to reduce endogeneity concerns.

– Tables 14 about here –

7.2 Matching of immigrants and natives

If the ex-ante screening costs are mostly fixed and if the same screening technology (such as setting up a hiring office) can be applied to immigrants and natives,[48] an additional insight of the screening explanation is that a larger share of immigrants will imply firms screening *also* for native workers. This will result in a higher probability of assortative matching between firms and *both* native and immigrant workers. In the top panel of Table 15 we use as dependent variable the assortative matching intensity between *native* workers and firms. We find a positive and statistically significant effect of immigration on the strength of firm-native worker matching in each specification.

– Table 15 about here –

In the bottom panel of Table 15 we conduct the same exercise but using only *immigrant* workers to compute our measures of positive assortative matching. As immigrant workers are usually more mobile across firms and their quality distribution more disperse we expect stronger assortative matching effect of migration on the sub-sample of migrant workers. This is confirmed by the results in Table 15, where the point estimates on the immigrant share are larger in magnitude for migrants than for natives matching measures.[49]

7.3 Immigration and recruitment personnel

While intensity of screening is hard to measure directly, one can observe the share of workers in each firm whose main task is to recruit people. The DADS data include very detailed information on the occupations of workers. In particular, two job titles described as "*specialist of recruitment and formation*" and "*specialist of human resources and recruitment*" are those that we will call "recruitment personnel" and we will use as indicator of the resources that a firm puts into screening new workers.[50]

[48]Figure B1 provides suggestive evidence of the fixed nature of screening costs.

[49]In a recent paper, Dostie, Li, Card & Parent (2021), the different sorting of immigrant and native workers across high- vs low-productive firms is used to explain a fraction of the wage gap between immigrant and native workers.

[50]The two specific codes of the French occupation classification (PCS 4-digit) are: (i) *Cadres spécialistes du recrutement et de la formation* (PCS 3722 in rev. 1982), (ii) *Cadres spécialistes des ressources humaines et du recrutement* (PCS 372c in rev. 2003). These are workers specifically dedicated to the recruitment process of the firm. Other workers occupations (within the HR division of firms), only marginally related to the recruitment process (i.e. translators) have other PCS codes in the French occupation classification and are not considered here as "recruitment personnel".

Results in Table 16 show how the share of recruitment personnel in firm's employment responds to immigration. Column (1) shows the positive effect of immigration on the share of recruitment personnel in the firm (average across firms of a given district). Since the number of workers can be an imprecise measure of the recruitment intensity, in column (2) of Table 16 we show that results still holds for the share of hours worked in recruitment personnel occupations (over the total hours worked in the firm). In columns (3) and (4) we approximate the screening effort of districts with the share of recruitment personnel workers (defined as the total number of those workers over total employment in the district) and the share of firms with at least one recruitment personnel worker in the district. Using these alternative proxies, the effect of immigration on these proxies of screening intensity is positive and significant.

– Tables 16 about here –

Finally, a piece of evidence consistent with screening cost having a significant fixed component is shown in Figure B1. Data from DARES (French Ministry of Labor) on the recruitment process of French firms in 2005 show that the ratio of hiring resources and total human resources workers decreases with the size of firms, implying that screening cost are a decreasing share of cost as firm size grow.

7.4 Workers' flows across firms

Positive complementarity between firm and worker quality implies that high-quality firms are those more likely to screen as they benefit the most from improving the quality of their matches. To this end, we test the effect of immigrant share on the number of high-quality workers moving from low- to high- quality firms and on the number of low-quality workers moving from high- to low-quality firms in a given district. Both moves are reasonable consequences of high-quality firms becoming more selective and attracting high quality while letting low quality workers go.[51] Already simple correlation statistics show that in districts experiencing larger than average increase in the share of immigrants over the period 1995-2005, 46.3% of total firm-to-firm workers moves followed a PAM pattern. In districts with migrant increases below the average, only the 37.6% of total firm-to-firm workers moves followed a PAM pattern.

[51] In Table A10 we show the number of workers that move across firms of different type each year. Workers that experienced unemployment spells larger than one year cannot be considered as movers for economic reasons, and are not included in these statistics.

More formally, Table 17 shows the 2SLS estimates of the impact of immigrant share on mobility of high- and low-quality workers across high- and low-quality firms. Entry (1) in the top row shows the effect of immigrants on the number of high-type workers moving from low- to high-type firms. These are high-quality workers newly hired by high-quality firms. The impact of immigration on this flow is significant, numerically large and positive. In contrast, immigration does not affect overall mobility between firms, because the effect on the number of high-quality workers attracted by low-quality firms, estimated in specification (2) of row 1, is not significant. The second row of the table shows less precisely estimated effect on flows of low type workers moving between either type of firms. Overall, the strongest impact of immigration, in terms of flows, is in making high-quality firms more likely to attract high-quality workers from lower-quality firms (see column 1 of the table). One standard deviation increase in the share of migrants in a district implies a 67% increase in the number of high-type movers from low- to high-productive firms. This suggests that stronger assortative matching induced by immigration is channelled by high-quality firms increasingly attracting high-quality workers.

– Tables 17 about here –

7.5 Immigration and screening cost across sectors

A final piece of evidence is to analyze whether, by classifying sectors according to proxies of screening costs, we find stronger effects of migration on PAM for sectors with smaller screening costs.

Using DARES (French Ministry of Labor) survey data on the recruitment process of firms in 2005, we build two proxies of sector-specific screening cost.[52] The first is the ratio between average number of recruiters and HR workers in the sector (dummy equal to one if above the median), capturing the labor costs of hiring. The second is the average number of days needed to recruit a worker in the sector. Both measures are meant to approximate the time and labor cost of the screening process in the sector. We interacted them with the share of immigrants in the districts (we use district-sector-year specific estimations as in section 6.3). Results in Table A11 clearly show a negative and significant coefficient on the interaction term. This implies that in sectors with smaller screening costs, exogenous inflows of immigrants increased more significantly the strength of PAM possibly as introducing additional screening was less expensive. Sectors with higher screening cost exhibit smaller effects of immigrants on the PAM of workers and firms.

[52] DARES data do not provide the firm identifier nor the district, hence we only construct sector-level measures.

8 Conclusions

This paper uses employer-employee matched data for the universe of French private-sector firms to identify a new effect of immigration on local economies. Larger inflows of immigrants across French districts are associated with a stronger positive assortative matching (PAM) between firms and workers. Using a shift-share instrument, tested using the recently proposed econometric checks of validity, we show that immigration increased the (positive) correlation between firm and workers' quality. We also show that immigration was associated with larger average firm profits, larger average wages and higher wage dispersion, all consequences of PAM when quality of workers and firms are complementary. This is a novel result in the literature. The immigration-induced PAM provides an offsetting mechanism for potential negative wage effects, adding a new reason why a large number of empirical papers finds that immigration has no negative impact on average wages.

The magnitude of the effect is economically significant: in districts where the share of immigrants grew by one percent of the population, the share of net positive assortative matches between firms and workers increased by 2.2 percentage points. This is a significant effect, as it represents a 3.8% increase in the average share of positive assortative matches (net of mismatches) across French local labor markets, about one-fourth of the 25-75 percentile difference in this measure across districts.

While there could be a number of explanations for this association, additional results support the idea that, when the skill dispersion of workers becomes larger, it is in the interest of high-quality firms to introduce (improve) screening and select the best workers, leaving the lower-quality workers to lower-quality firms. As immigrants' workers are shown to have a larger variance in their quality, when their share of local employment increases, high quality firms increase the amount of screening and attract higher quality workers. Consistently, we find that: (i) in regions where immigrants' quality is more dispersed the impact of immigrants on PAM intensity is larger, (ii) firms expand their "recruiting personnel", a proxy for screening effort, when immigration increases, (iii) high-quality firms attract more high-quality workers in regions with higher immigration and (iv) sectors with lower screening costs and more immigrants experience a stronger PAM response to the inflow of new immigrants.

The screening mechanism implies larger average wages and higher firm profit, but also higher wage dispersion and a potentially negative effect on wages of lower-quality workers. We think that the worker-firm interactions and the margin of firm responses highlighted in this paper are important to capture a full set of effects of immigration, which could be overlooked in the canonical model.

Bibliography

Abowd, J. M., Kramarz, F. & Margolis, D. N. (1999), 'High Wage Workers and High Wage Firms', *Econometrica* **67**(2), 251–334.

Acemoglu, D. (1997), 'Matching, heterogeneity, and the evolution of income distribution', *Journal of Economic Growth* **2**(1), 61–92.

Acemoglu, D. (1999), 'Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence', *American Economic Review* **89**(5), 1259–1278.

Albert, C. & Monras, J. (2018), Immigration and Spatial Equilibrium: the Role of Expenditures in the Country of Origin, Cepr discussion papers, C.E.P.R. Discussion Papers.

Albrecht, J. & Vroman, S. (2002), 'A Matching Model with Endogenous Skill Requirements', *International Economic Review* **43**(1), 283–305.

Autor, D. H., Dorn, D. & Hanson, G. H. (2013), 'The China Syndrome: Local Labor Market Effects of Import Competition in the United States', *American Economic Review* **103**(6), 2121–2168.

Bartolucci, C., Devicienti, F. & Monzón, I. (2018), 'Identifying Sorting in Practice', *American Economic Journal: Applied Economics* **10**(4), 408–438.

Battisti, M., Felbermayr, G., Peri, G. & Poutvaara, P. (2018), 'Immigration, Search and Redistribution: A Quantitative Assessment of Native Welfare', *Journal of the European Economic Association* **16**(4), 1137–1188.

Beerli, A., Ruffner, J., Siegenthaler, M. & Peri, G. (2021), 'The abolition of immigration restrictions and the performance of firms and workers: Evidence from switzerland', *American Economic Review* **111**(3), 976–1012.

Bernard, A. B., Jensen, J. B., Redding, S. J. & Schott, P. K. (2007), 'Firms in International Trade', *Journal of Economic Perspectives* **21**(3), 105–130.

Bianchi, M., Buonanno, P. & Pinotti, P. (2012), 'Do Immigrants Cause Crime?', *Journal of the European Economic Association* **10**(6), 1318–1347.

Bombardini, M., Orefice, G. & Tito, M. D. (2019), 'Does Exporting Improve Matching? Evidence from French Employer-Employee Data', *Journal of International Economics* **117**, 229–241.

Bonhomme, S., Lamadon, T. & Manresa, E. (2019), 'A Distributional Framework for Matched Employer Employee Data', *Econometrica* **87**(3), 699–739.

Borjas, G. J. (1987), 'Self-Selection and the Earnings of Immigrants', *American Economic Review* **77**(4), 531–553.

Burzynski, M. & Gola, P. (2019), Mexican Migration to the United States: Selection, Assignment, and Welfare, LISER Working Paper Series 2019-10, LISER.

Card, D. (2001), 'Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration', *Journal of Labor Economics* **19**(1), 22–64.

Card, D. (2005), 'Is the New Immigration Really so Bad?', *Economic Journal* **115**(507), 300–323.

Card, D., Cardoso, A. R., Heining, J. & Kline, P. (2018), 'Firms and Labor Market Inequality: Evidence and Some Theory', *Journal of Labor Economics* **36**(S1), 13–70.

Card, D., Heining, J. & Kline, P. (2013), 'Workplace Heterogeneity and the Rise of West German Wage Inequality', *The Quarterly Journal of Economics* **128**(3), 967–1015.

Chassamboulli, A. & Palivos, T. (2014), 'A Search-Equilibrium Approach To The Effects Of Immigration On Labor Market Outcomes', *International Economic Review* **55**, 111–129.

Combes, P.-P., Duranton, G. & Gobillon, L. (2008), 'Spatial wage disparities: Sorting matters!', *Journal of Urban Economics* **63**(2), 723–742.

Conley, T. G., Hansen, C. B. & Rossi, P. E. (2012), 'Plausibly Exogenous', *The Review of Economics and Statistics* **94**(1), 260–272.

Dauth, W., Findeisen, S., Moretti, E. & Suedekum, J. (2022), 'Matching in Cities', *Journal of the European Economic Association* (forthcoming).

Davidson, C., Heyman, F., Matusz, S., Sjoholm, F. & Zhu, S. C. (2012), 'Liberalized Trade and Worker-Firm Matching', *American Economic Review* **102**(3), 429–434.

Davidson, C., Heyman, F., Matusz, S., Sjoholm, F. & Zhu, S. C. (2014), 'Globalization and imperfect labor market sorting', *Journal of International Economics* **94**(2), 177–194.

Davidson, C., Matusz, S. J. & Shevchenko, A. (2008), 'Globalization and firm level adjustment with imperfect labor markets', *Journal of International Economics* **75**(2), 295–309.

De La Roca, J. & Puga, D. (2017), 'Learning by Working in Big Cities', *Review of Economic Studies* **84**(1), 106–142.

de Melo, R. L. (2018), 'Firm Wage Differentials and Labor Market Sorting: Reconciling Theory and Evidence', *Journal of Political Economy* **126**(1), 313–346.

Diamond, P. A. (1982), 'Wage determination and efficiency in search equilibrium', *The Review of Economic Studies* **49**(2), 217–227.

Dostie, B., Li, J., Card, D. & Parent, D. (2021), 'Employer policies and the immigrantвЃYnative earnings gap', *Journal of Econometrics* (forthcoming).

Dustmann, C., Frattini, T. & Preston, I. P. (2013), 'The Effect of Immigration along the Distribution of Wages', *Review of Economic Studies* **80**(1), 145–173.

Edo, A. (2019), 'The Impact of Immigration on Wage Dynamics: Evidence from the Algerian Independence War', *Journal of the European Economic Association* **18**(6), 3210–3260.

Eeckhout, J. & Kircher, P. (2011), 'Identifying Sorting–In Theory', *Review of Economic Studies* **78**(3), 872–906.

Eeckhout, J. & Kircher, P. (2018), 'Assortative matching with large firms', *Econometrica* **86**(1), 85–132.

Friedberg, R. M. & Hunt, J. (1995), 'The Impact of Immigrants on Host Country Wages, Employment and Growth', *Journal of Economic Perspectives* **9**(2), 23–44.

Gautier, P. A. & Teulings, C. N. (2006), 'How Large are Search Frictions?', *Journal of the European Economic Association* **4**(6), 1193–1225.

Glaeser, E. L. & Mare, D. C. (2001), 'Cities and Skills', *Journal of Labor Economics* **19**(2), 316–342.

Goldsmith-Pinkham, P., Sorkin, I. & Swift, H. (2020), 'Bartik instruments: What, when, why, and how', *American Economic Review* **110**(8), 2586–2624.

Guadalupe, M., Kuzmina, O. & Thomas, C. (2012), 'Innovation and Foreign Ownership', *American Economic Review* **102**(7), 3594–3627.

Helpman, E., Itskhoki, O. & Redding, S. (2010), 'Inequality and Unemployment in a Global Economy', *Econometrica* **78**(4), 1239–1283.

Jaeger, D. A., Ruist, J. & Stuhler, J. (2018), Shift-Share Instruments and the Impact of Immigration, NBER Working Papers 24285, National Bureau of Economic Research, Inc.

Kline, P., Saggio, R. & Sølvsten, M. (2020), 'LeaveвΓΘOut Estimation of Variance Components', *Econometrica* **88**(5), 1859–1898.

Kremer, M. (1993), 'The O-ring theory of economic development', *The Quarterly Journal of Economics* pp. pp. 551–575.

Lewis, E. & Peri, G. (2015), Immigration and the Economy of Cities and Regions, *in* G. Duranton, J. V. Henderson & W. C. Strange, eds, 'Handbook of Regional and Urban Economics', Vol. 5 of *Handbook of Regional and Urban Economics*, Elsevier, chapter 0, pp. 625–685.

Mitaritonna, C., Orefice, G. & Peri, G. (2017), 'Immigrants and firms? outcomes: Evidence from France', *European Economic Review* **96**(C), 62–82.

Moretti, E. (2004), 'Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions', *American Economic Review* **94**(3), 656–690.

Ottaviano, G. I. P. & Peri, G. (2012), 'Rethinking The Effect Of Immigration On Wages', *Journal of the European Economic Association* **10**(1), 152–197.

Peri, G. (2012), 'The Effect Of Immigration On Productivity: Evidence From U.S. States', *The Review of Economics and Statistics* **94**(1), 348–358.

Peri, G. (2016), 'Immigrants, Productivity, and Labor Markets', *Journal of Economic Perspectives* **30**(4), 3–30.

Peri, G. & Sparber, C. (2009), 'Task Specialization, Immigration, and Wages', *American Economic Journal: Applied Economics* **1**(3), 135–169.

Pischke, J.-S. & Velling, J. (1997), 'Employment Effects Of Immigration To Germany: An Analysis Based On Local Labor Markets', *The Review of Economics and Statistics* **79**(4), 594–604.

van Kippersluis, H. & Rietveld, C. A. (2018), 'Beyond plausibly exogenous', *Econometrics Journal* **21**(3), 316–331.

Wooldridge, J. M. (2009), 'On estimating firm-level production functions using proxy variables to control for unobservables', *Economics Letters* **104**(3), 112–114.

Tables and Figures

Table 1: Immigrant workers in France in the period 1995-2005.

	1995	2005	95-05 % change
Share of immigrants (%)	6.2	9.7	54.6
Average age of immigrants	40.9	41.6	1.7
Sh. high-skill white-collar immigrants (%)	20.8	31.5	51.4
Sh. low-skill white-collar immigrants (%)	15.7	18.5	18.6
Sh. high-skill blue-collar immigrants (%)	23.4	17.1	-27.3
Sh. low-skill blue-collar immigrants (%)	39.6	32.4	-18.1

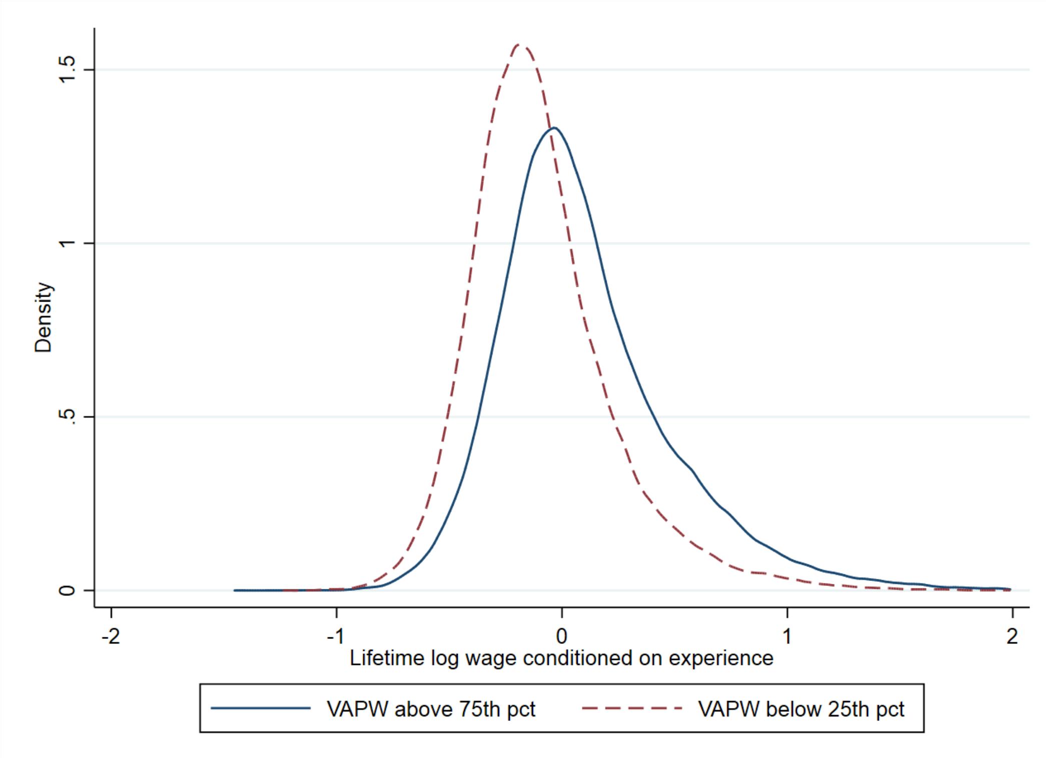
Notes: We use the Eurofond conversion table (available here `https://www.eurofound.europa.eu/surveys/ewcs/2005/classification`) to map the 2-digit PCS French occupation categories into the macro occupation-education categories adopted in the table.

Table 2: In-sample descriptive statistics.

year	# workers with ID	# firms	# movers	Median firm size
1996	119956	37516	824	20
1997	119851	38083	4175	20
1998	115805	37599	5836	21
1999	115943	37851	9085	20
2000	111698	37011	7538	20
2001	110331	36968	8172	21
2002	219805	55941	9148	15
2003	209375	57229	7295	14
2004	210944	57143	10776	14
2005	199443	54188	13347	14

Notes: In sample descriptive statistics on the number of workers with ID are based on DADS panel data. The number of firms and the number of movers are obtained after joining DADS panel and FICUS/FARE data.

Figure 1: Distribution of worker type by high- vs. low-productivity firms.



Source: Authors calculations on DADS and FICUS/FARE data. *Note*: Worker type approximated by lifetime conditioned wage. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects).

Table 3: Share of workers of high/low ability employed at firm with high/low value added per worker.

	All Districts			
	Year 1995		**Year 2005**	
	High-Prod Firms	Low-Prod Firms	High-Prod Firms	Low-Prod Firms
High-Ability workers	28.3	21.5	28.3	21.6
Low-Ability workers	20.5	29.5	20.8	29.2

Notes: The calculations use the matched employer-employee French data provided by INSEE for the years 1995 and 2005. The classification of worker types in this table follows their lifetime wage (conditional on worker's age), while value added per worker is used as a proxy for the firm type. Each cell reports the percentage of workers of a given level of ability (high vs low) employed at a firm with high or low productivity. High- and low-type workers and firms refer respectively to workers and firm with type above and below the district average. The main diagonal represents the strength of assortative matching while the anti-diagonal represents the extent of mismatch in local labor market. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects).

Table 4: Empirical distribution characteristics for immigrant and native workers types

		Natives	Immigrants
Lifetime conditioned Wage	Average	0.00	-0.02
	Standard Deviation	0.37	0.40
	Interquartile Range	0.41	0.43
	Top-1 percentile	1.21	1.31
	Bottom-1 percentile	-0.67	-0.71
	Kolmogorov-Smirnov test (p-value)	0.000	
AKM decomposition	Average	-0.05	-0.19
	Standard Deviation	0.78	0.82
	Interquartile Range	1.16	1.27
	Top-1 percentile	1.88	1.89
	Bottom-1 percentile	-1.42	-1.56
	Kolmogorov-Smirnov test (p-value)	0.000	

Notes: The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). The null hypothesis of the Kolmogorov-Smirnov test is the equality of distribution between native and migrant worker types.

Table 5: Immigrant share and moments of workers types distribution across districts.

Moment of worker type distribution	5^{th} pctile	10^{th} pctile	25^{th} pctile	75^{th} pctile	90^{th} pctile	95^{th} pctile
Immi Share	-0.053	-0.066**	-0.048**	0.057**	0.126***	0.051
	(0.037)	(0.031)	(0.019)	(0.023)	(0.046)	(0.070)
Observations	1,012	1,012	1,012	1,012	1,012	1,012

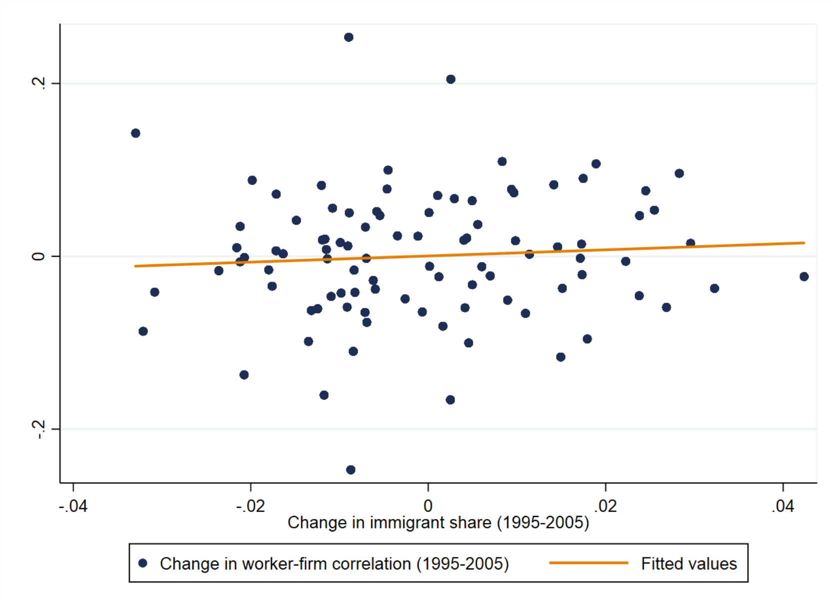
Note: Worker types approximated by lifetime conditioned wage. All regressions include region-by-year fixed effects, the average worker type in the district, and the district-year specific controls described in the empirical strategy. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table 6: Strength of assortative matching and value added per worker in the district.

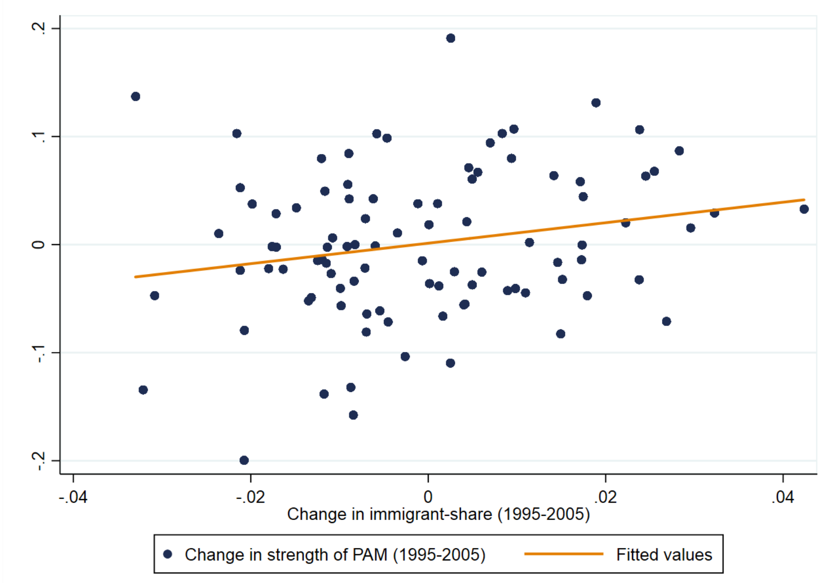
	Value Added per worker			
	(1)	(2)	(3)	(4)
Rank Corr. VAPW-Lifetime Wage	0.209***			
	(0.041)			
Rank Corr. VAPW-AKM		0.195***		
		(0.051)		
Strength PAM VAPW-Lifetime Wage			0.166***	
			(0.042)	
Strength PAM VAPW-AKM				0.232***
				(0.052)
District FE	yes	yes	yes	yes
Region-by-Year FE	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012
R-squared	0.998	0.998	0.998	0.998

Note: Dependent variable is the average value added per worker (VAPW) across firms within a district. All regressions include district and region-by-year fixed effects. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Figure 2: Change in migrant population and PAM across districts.



(a) Change in immigrant share and Worker-Firm type correlation. Worker type: lifetime conditional wage.



(b) Change in immigrant share and strength of PAM. Worker type: lifetime conditional wage.

Source: Authors' calculation DADS data for the period 1995-2005. *Note*: Variables conditioned on region fixed effects. Department of Aude dropped as outlier.

Table 7: Test for the validity of the Instrumental Variable.

	Δ ln Emplo 1995-1994	Δ ln Wage 1995-1994	Δ ln Emplo 1990-1982	Δ ln Nat. Emp. 1990-1982	Δ ln Wage 1990-1982	Δ ln Wage Nat. 1990-1982
Δ IV (05-95)	0.839	-0.551	0.185	0.089	2.269	2.523
	(0.551)	(0.722)	(0.514)	(0.542)	(1.490)	(1.645)
Source	DADS	DADS	LFS	LFS	LFS	LFS
Observations	92	92	92	92	92	92
R-squared	0.878	0.403	0.290	0.293	0.285	0.268

Notes: All regressions include region fixed effects. Difference in the average wage 1990-1982 from LFS bases on difference in the wage bin (with bins based on deciles of hourly wage distribution). Robust standard errors in parenthesis.

Table 8: Immigrant share and assortative matching, OLS baseline specification.

Dep Var:	*Rank Correlation*		*Strength PAM*		*Firm Profit*
	(1)	(2)	(3)	(4)	(5)
Immi Share	0.450**	-0.249	0.518***	-0.344	1.275
	(0.203)	(0.222)	(0.190)	(0.212)	(2.392)
Nat Employment (ln)	-0.028	0.003	-0.009	-0.030	-0.963*
	(0.039)	(0.044)	(0.041)	(0.042)	(0.582)
Firms Concentration	-0.078	-1.133***	0.086	-0.405	-2.734
	(0.251)	(0.258)	(0.249)	(0.268)	(4.022)
Skilled share	0.259***	0.018	0.122	-0.107	1.658
	(0.118)	(0.143)	(0.115)	(0.145)	(1.279)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM	
District FE	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012	1,003
R-squared	0.796	0.843	0.729	0.767	0.977

Notes: Dependent variables are respectively the rank correlation between worker and firm type, the strength of positive assortative matching, and the average firms' profits in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and (iii) the share of skilled workers in the districts. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$. Models are weighted by the number of firms in the district.

Table 9: Immigrant share and assortative matching, 2SLS baseline specification.

Dep Var:	*Rank Correlation*		*Strength PAM*		*Firm Profit*
	(1)	(2)	(3)	(4)	(5)
Immi Share	2.752**	2.866**	2.280**	2.926**	14.327*
	(1.200)	(1.195)	(0.966)	(1.176)	(7.651)
Nat Employment (ln)	-0.072	0.023	-0.061	-0.031	-0.819**
	(0.054)	(0.042)	(0.044)	(0.049)	(0.403)
Firms Concentration	0.757***	-0.238	0.607**	0.210	7.919
	(0.274)	(0.238)	(0.262)	(0.254)	(5.191)
Skilled share	0.425**	0.349*	0.257	0.345*	1.907
	(0.179)	(0.191)	(0.156)	(0.197)	(1.197)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM	
District FE	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012	1,003
R-squared	0.142	0.090	0.172	0.088	0.843
First stage coeff	0.121***	0.121***	0.121***	0.121***	0.122***
F-stat	16.64	16.64	16.64	16.64	15.33
Partial R-sq	0.047	0.047	0.047	0.047	0.046

Notes: Dependent variables are respectively the rank correlation between worker and firm type, the strength of positive assortative matching, and the average firms' profits in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and the (iii) share of skilled workers in the districts. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table 10: Immigrant share and assortative matching, 2SLS using alternative IVs.

Dep Var:	*Rank Correlation*		*Strength PAM*		*Firm Profit*
	(1)	(2)	(3)	(4)	(5)
			Panel a: IV based on migration inflows in France		
Immi Share	2.298*	1.709	2.001*	0.637	25.565**
	(1.295)	(1.231)	(1.124)	(1.100)	(12.792)
Observations	1,012	1,012	1,012	1,012	1,003
First stage coeff.	0.284***	0.284***	0.284***	0.284***	0.278***
F-stat	9.28	9.28	9.28	9.28	8.56
Partial R-sq	0.031	0.031	0.031	0.031	0.030
			Panel b: IV based on migration inflows in other EU-15		
Immi Share	2.331*	2.527*	2.960**	3.037**	7.002
	(1.353)	(1.326)	(1.198)	(1.350)	(7.269)
Observations	1,012	1,012	1,012	1,012	1,003
First stage coeff.	0.049***	0.049***	0.049***	0.049***	0.050***
F-stat	14.95	14.95	14.95	14.95	14.37
Partial R-sq	0.036	0.036	0.036	0.036	0.036
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM	
District FE	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes

Notes: Alternative instrumental variables base on geographic distribution of immigrants across districts in 1982 augmented by the: (i) observed migration inflows in France by origin country (i.e. standard shift-share approach) in panel a; (ii) observed inflows of migrants into EU-15 destinations (excluded France) in panel b. Dependent variables are respectively the rank correlation between worker and firm type, the strength of positive assortative matching, and the average firms' profits in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and (iii) the share of skilled workers in the districts. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table 11: Immigrant share and assortative matching. Robustness check controlling for exports, capital intensity and intermediate inputs intensity.

Dep Var:	*Rank Correlation*		*Strength PAM*		*Firm Profit*
	(1)	(2)	(3)	(4)	(5)
Immi Share	2.553**	3.182***	1.974**	2.911***	21.643***
	(1.100)	(1.102)	(0.892)	(1.065)	(7.642)
Nat Employment (ln)	-0.079	0.039	-0.068	-0.021	-0.679
	(0.054)	(0.042)	(0.043)	(0.049)	(0.413)
Firms Concentration	0.689**	-0.888***	0.632**	-0.218	-4.738
	(0.309)	(0.261)	(0.303)	(0.265)	(4.756)
Skilled share	0.420**	0.390**	0.235	0.348*	3.141***
	(0.174)	(0.189)	(0.152)	(0.192)	(1.205)
Exports (ln)	0.004	0.022***	0.001	0.015***	0.378***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.044)
K/L	-0.005**	0.000	-0.004*	0.000	-0.091***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.025)
Intermediates/Tot Prod	0.001	-0.007	-0.001	-0.009***	0.061*
	(0.005)	(0.005)	(0.003)	(0.003)	(0.031)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM	
District FE	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012	1,003
R-squared	0.164	0.081	0.198	0.109	0.854
First stage coeff.	0.134***	0.134***	0.134***	0.134***	0.135***
F-stat	20.49	20.49	20.49	20.49	19.25
Partial R-sq	0.052	0.052	0.052	0.052	0.051

Notes: Dependent variables are respectively the rank correlation between worker and firm type, the strength of positive assortative matching, and the average firms' profits in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms, (iii) share of skilled workers in the districts, (iv) total exports of firms in the district, (v) average capital intensity of firms in the district, and (vi) the average intermediate input intensity of firms in the district. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$..

Table 12: Immigrant share and assortative matching, district-sector specific regressions.

Dep Var:	*Rank Correlation*		*Strength PAM*		*Firm Profit*
	(1)	(2)	(3)	(4)	(5)
	Panel a: Robustness check with sector-year FE				
Immi Sh.	2.297***	0.930	2.994**	4.034**	7.160*
	(0.812)	(0.674)	(1.461)	(1.631)	(4.135)
Observations	14,056	14,056	14,056	14,056	13,801
First stage coeff.	0.119***	0.119***	0.119***	0.119***	0.117***
F-stat	22.10	22.10	22.10	22.10	21.40
Partial R-sq	0.045	0.045	0.045	0.045	0.044
	Panel b: Interacting with industry immi intensity				
Immi Sh.	2.219***	0.868	2.978**	4.051**	6.317
	(0.823)	(0.677)	(1.456)	(1.646)	(3.854)
Immi Sh. $\times$ Industry Immi Int.	0.461***	0.297***	0.233**	0.092	1.314**
	(0.100)	(0.086)	(0.111)	(0.122)	(0.581)
Observations	13,947	13,947	13,947	13,947	13,801
First stage coeff. immi share	0.119***	0.119***	0.119***	0.119***	0.118***
First stage coeff. interaction	0.392***	0.392***	0.392***	0.392***	0.392***
Joint F-stat	11.11	11.11	11.11	11.11	10.76
Partial R-sq	0.045	0.045	0.045	0.045	0.044
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM	
District FE	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes
Sector-Year FE	yes	yes	yes	yes	yes

Notes: Dependent variables are respectively the rank correlation between worker and firm type, the strength of positive assortative matching, and the average firms' profits in each district-sector-year. Dependent variables are built at district-sector-year level. Immigrant share and control variables are at district-year level. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and the (iii) share of skilled workers in the districts. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table 13: Wage and wage inequality regressions, baseline 2SLS specification.

Dep Var:	$Ln(wage_{dt})$	$Ln(wage^H_{dt})$	$Ln(wage^L_{dt})$	$[Ln(wage^H_{dt})$ - $Ln(wage^L_{dt})]$	
	(1)	(2)	(3)	(4)	(5)
Immi Share	0.841*	1.387**	-0.088	1.475**	1.966**
	(0.439)	(0.653)	(0.250)	(0.657)	(0.881)
Worker Type		Lifetime wage		Lifetime wage	AKM
District FE	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes
District-Year controls	yes	yes	yes	yes	yes
Other district controls	yes	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012	1,012
First stage coeff.		0.134***		0.134***	
F-stat		20.49		20.49	

Notes: In columns (1)-(3) dependent variable is the (log) average wage of all workers, high- and low-quality workers in each district-year (i.e. workers with type above and below the average in the district). In columns (4)-(5) the dependent variable is the difference in (log) average wage between high- and low-type workers in each district-year. District-year specific controls always included are: (i) number of native workers in the district, (ii) concentration of firms, (iii) share of skilled workers in the districts, (iv) district's total exports, (v) average capital intensity, and (vi) intermediate inputs intensity. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table 14: The heterogeneous effect of migration on Positive Assortative Matching, 2SLS baseline specification.

Dep Var:	*Rank Correlation*				*Strength PAM*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immi sh × below median IQR	2.449*		2.798*		2.059*		3.541**	
	(1.451)		(1.444)		(1.199)		(1.434)	
Immi sh × above median IQR	3.087***		2.942**		2.525***		2.245*	
	(1.192)		(1.253)		(0.954)		(1.181)	
Immi sh × below median min-max		0.816		2.110		1.166		1.166
		(2.879)		(2.676)		(2.493)		(2.515)
Immi sh × above median min-max		2.789**		2.881**		2.301**		2.960***
		(1.155)		(1.179)		(0.954)		(1.149)
Worker Type	Lifetime wage		AKM		Lifetime wage		AKM	
District FE	yes	yes	yes	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
District-Year controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012
First stage coeff below IQR	0.140***		0.140***		0.140***		0.140***	
First stage coeff above IQR	0.111***		0.111***		0.111***		0.111***	
First stage coeff below min-max		0.080*		0.080*		0.080*		0.080*
First stage coeff above min-max		0.136***		0.136***		0.136***		0.136***
F-stat	7.105	1.49	7.105	1.49	7.105	1.49	7.105	1.49

Notes: Dependent variables are respectively the rank correlation between worker and firm type, and the strength of positive assortative matching in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and (iii) the share of skilled workers in the districts. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table 15: Native vs. Migrant workers assortative matching.

Dep Var:	*Rank Correlation*		*Strength PAM*	
	(1)	(2)	(3)	(4)
		Native workers only		
Immi Share	2.579**	2.082*	1.749*	2.400**
	(1.192)	(1.142)	(0.956)	(1.179)
Observations	1,012	1,012	1,012	1,012
First stage coeff.	0.121***	0.121***	0.121***	0.121***
F-stat	16.64	16.64	16.64	16.64
Partial R-sq	0.047	0.047	0.047	0.047
		Migrant workers only		
Immi Share	7.978***	1.656	10.535***	9.792***
	(2.479)	(1.917)	(3.018)	(2.878)
Observations	1,012	1,012	1,005	1,005
First stage coeff.	0.121***	0.121***	0.121***	0.121***
F-stat	16.64	16.64	16.64	16.64
Partial R-sq	0.047	0.047	0.047	0.047
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM
District FE	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes
District controls	yes	yes	yes	yes

Notes: Dependent variables are respectively the rank correlation between native/migrant worker and firm type and the strength of positive assortative matching in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and (iii) the share of skilled workers in the districts. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$..

Table 16: Immigrant share and the recruitment personnel (RP) intensity of districts.

	Share RP workers in the firm (avg in the district)	Share RP hours in the firm (avg in the district)	Share of RP workers in the district	Sh. Firms with at least one RP worker
Immi Share	0.007*	0.008*	0.095***	0.013**
	(0.004)	(0.004)	(0.035)	(0.006)
District FE	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes
District-Year controls	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012
First stage coeff.	0.121***	0.121***	0.121***	0.121***
F-stat	16.64	16.64	16.64	16.64

Notes: Dependent variables are: (i) the share of recruitment personnel workers over total employees in the firm (average across firms in the district), (ii) the share of hours worked in recruitment personnel positions in the firm (average across firms in the district), (iii) the share of recruitment personnel workers in the district, and (iv) the share of firms with at least one recruitment personnel worker in the district. District-year specific controls are: number of native workers in the district, concentration of firms and the share of skilled workers in the districts. Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

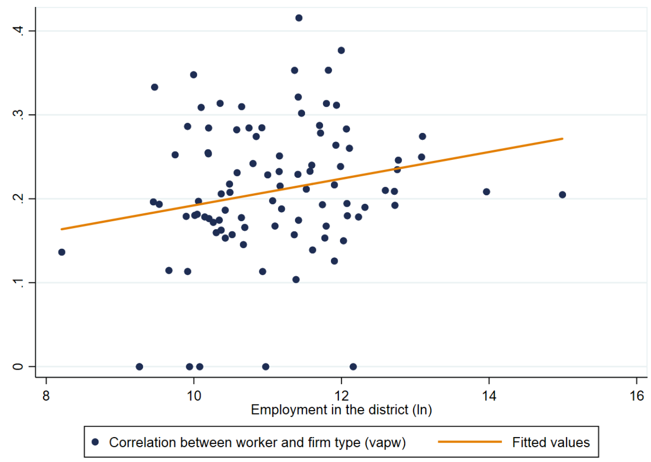
Table 17: Immigrant share and movers by worker-type across firms of different type.

	# *High-type movers*	
	from *low* to *high* type firm (1)	from *high* to *low* type firm (2)
Immi Share	16.906*	4.017
	(10.041)	(10.887)
	# *Low-type movers*	
	from *high* to *low* type firm (1)	from *low* to *high* type firm (2)
Immi Share	11.598	3.397
	(10.455)	(9.531)
Worker Type	Lifetime	
Firm Type	Value Added per Worker	
District FE	yes	yes
Region-Year FE	yes	yes
District-Year controls	yes	yes
Observations	1,012	1,012
First stage coeff.	0.121***	
F-stat	16.64	
Partial R-squared	0.047	

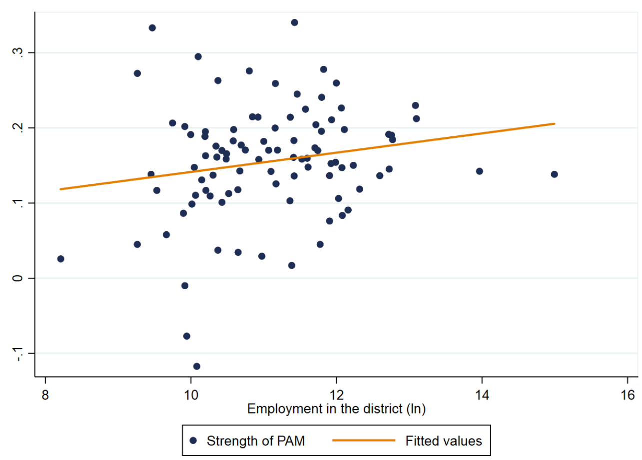
Notes: Dependent variables are the number of high- and low-type worker (in log) changing employer (i.e. *siren* code) and moving across firms of different type. High (low) type firms are firms with value added per worker above (below) the median. District-year specific controls are: number of native workers in the district, concentration of firms and the share of skilled workers in the districts. The lifetime conditioned wage used to approximate the worker type is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

A Appendix tables (For Online Publication)

Figure A1: Total employment and PAM across districts.



(a) Employment and Worker-Firm type correlation. Worker type: lifetime wage.



(b) Employment and strength of PAM. Worker type: lifetime wage.

Source: Authors calculations on DADS and Ficus/Fare data. *Note*: Positive Assortative Matching approximated with the rank correlation between worker and firm type within a district (panel a) and the strength of PAM (panel b). Worker type approximated by conditioned lifetime wage. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Department of Lozére dropped as outlier.

Table A1: Immigrants and the distribution of workers types.

	Std Dev Worker Type	Inter-quartile Worker Type	Min-Max diff. Worker Type
Immi Share	0.088***	0.260***	3.604***
	(0.032)	(0.054)	(0.949)
Observations	1,012	1,012	1,012

Note: All regressions include region-by-year fixed effects and the district-year specific controls described in the empirical strategy. Worker type approximated by lifetime conditioned wage. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A2: Validity of the IV. Correlation between the initial strength of PAM and change in the IV.

	Rank Correlation 1995		Strength PAM 1995	
Δ IV (2005-1995)	0.164	0.295	0.093	0.086
	(0.319)	(0.327)	(0.283)	(0.343)
Source	DADS	DADS	DADS	DADS
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM
Observations	92	92	92	92
R-squared	0.275	0.394	0.274	0.393

Notes: All regressions include region fixed effects. Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A3: Immigrant share and assortative matching, weighted 2SLS estimations.

Dep Var:	*Rank Correlation*		*Strength PAM*		*Firm Profit*
	(1)	(2)	(3)	(4)	(5)
Immi Share	3.765***	4.404**	2.964***	3.893**	4.176
	(1.346)	(2.041)	(1.042)	(1.904)	(8.153)
Nat Employment (ln)	0.035	0.092	0.037	0.051	-0.905*
	(0.058)	(0.087)	(0.048)	(0.080)	(0.520)
Firms Concentration	-0.205	-1.312***	-0.008	-0.567*	-2.837
	(0.286)	(0.340)	(0.244)	(0.324)	(3.371)
Skilled share	0.707***	0.648**	0.452**	0.466	2.053
	(0.223)	(0.312)	(0.189)	(0.308)	(1.463)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM	
District FE	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012	1,003
First stage coeff.	0.112**	0.112**	0.112**	0.112**	0.114**
F-stat	6.51	6.51	6.51	6.51	6.35
Partial R-sq	0.052	0.052	0.052	0.052	0.052

Notes: Weights are the number of firms in the district. Dependent variables are respectively the rank correlation between worker and firm type, the strength of positive assortative matching, and the average firms' profits in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and (iii) the share of skilled workers in the districts. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A4: Robustness check using alternative proxies of firm and worker type.

Dep Var:	*Rank Correlation*		*Strength PAM*	
	(1)	(2)	(3)	(4)
	Co-worker type as proxy for firm type			
Immi Share	19.241***	0.164	0.951*	1.770***
	(5.948)	(3.069)	(0.533)	(0.643)
	TFP as proxy for firm type			
Immi Share	2.207*	1.056	3.023***	1.281
	(1.244)	(0.946)	(1.069)	(0.869)
	AKM firm FE as proxy for firm type			
Immi Share	-0.767	4.444***	-0.942	0.919
	(0.867)	(1.158)	(1.009)	(1.145)
	Worker type conditioned on worker's occupation			
Immi Share	0.747	2.849**	0.507	2.774**
	(1.126)	(1.194)	(0.960)	(1.170)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM
District FE	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes
District controls	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012
First stage coeff.	0.121***			
F-stat	16.64			

Notes: Dependent variables are respectively the rank correlation between worker and firm type and the strength of positive assortative matching in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms, (iii) share of skilled workers in the districts. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A5: Robustness check excluding district-year controls.

Dep Var:	*Rank Correlation*		*Strength PAM*	
	(1)	(2)	(3)	(4)
Immi Share	2.403**	2.910**	2.009**	2.788**
	(1.161)	(1.199)	(0.945)	(1.160)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM
District FE	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes
District-Year controls	no	no	no	no
Observations	1,012	1,012	1,012	1,012
First stage coeff.	0.121***	0.121***	0.121***	0.121***
F-stat	16.49	16.49	16.49	16.49
Partial R-sq	0.046	0.046	0.046	0.046

Notes: Dependent variables are respectively the rank correlation between worker and firm type and the strength of positive assortative matching in each district-year. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A6: Robustness check including district specific trend.

Dep Var:	*Rank Correlation*		*Strength PAM*		*Firm Profit*
	(1)	(2)	(3)	(4)	(5)
Immi Share	2.641**	2.796**	2.182**	2.845**	13.767*
	(1.190)	(1.185)	(0.960)	(1.165)	(7.696)
Nat Employment (ln)	-0.063	0.030	-0.055	-0.024	-0.819**
	(0.056)	(0.043)	(0.046)	(0.051)	(0.410)
Firms Concentration	0.745***	-0.249	0.595**	0.198	7.891
	(0.272)	(0.237)	(0.261)	(0.254)	(5.177)
Skilled share	0.414**	0.340*	0.248	0.337*	1.840
	(0.182)	(0.192)	(0.159)	(0.199)	(1.192)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM	
District Trend	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012	1,003
First stage coeff.	0.124***	0.124***	0.124***	0.124***	0.122***
F-stat	15.86	15.86	15.86	15.86	14.96

Notes: Dependent variables are respectively the rank correlation between worker and firm type, the strength of positive assortative matching, and the average firms' profits in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and the (iii) share of skilled workers in the districts. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A7: Robustness check excluding micro and very large firms.

Dep Var:	*Rank Correlation*		*Strength PAM*	
	(1)	(2)	(3)	(4)
Immi Share	4.779***	4.511***	1.994**	3.068***
	(1.417)	(1.471)	(0.936)	(1.189)
Nat Employment (ln)	0.019	0.024	-0.068	-0.052
	(0.060)	(0.052)	(0.045)	(0.057)
Firms Concentration	1.392***	0.720***	0.685***	0.516*
	(0.331)	(0.279)	(0.250)	(0.275)
Skilled share	0.694***	0.326	0.277*	0.376
	(0.223)	(0.226)	(0.147)	(0.216)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM
District FE	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012
First stage coeff.	0.121***	0.121***	0.121***	0.121***
F-stat	16.64	16.64	16.64	16.64
Partial R-sq	0.047	0.047	0.047	0.047

Notes: Dependent variables are respectively the rank correlation between worker and firm type and the strength of positive assortative matching in each district-year. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms, (iii) share of skilled workers in the districts. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A8: Alternative correlation measures to compute PAM.

Dep Var:	*Rank Correlation*		*Pearson Correlation*	
	(1)	(2)	(3)	(4)
Immi Share	2.891***	3.617***	2.127**	2.664**
	(1.029)	(1.246)	(0.977)	(1.091)
Nat Employment (ln)	-0.051	-0.008	-0.045	0.033
	(0.044)	(0.045)	(0.042)	(0.041)
Firms Concentration	0.697***	0.005	0.655***	0.102
	(0.251)	(0.262)	(0.234)	(0.260)
Skilled share	0.439***	0.398**	0.399**	0.320*
	(0.158)	(0.196)	(0.156)	(0.178)
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM
District FE	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes
District-Year controls	yes	yes	yes	yes
Observations	1,012	1,012	1,012	1,012
First stage coeff.[a]	0.121***	0.121***	0.121***	0.121***
F-stat	16.64	16.64	16.64	16.64
Partial R-sq	0.047	0.047	0.047	0.047

Notes: Dependent variables are respectively the rank correlation between worker and firm type abstracting from the significance (columns 1-2), the Pearson correlation index between worker and firm type (columns 3-4). District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and (iii) the share of skilled workers in the districts. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A9: Immigrant share and assortative matching with plausibly exogenous instrument.

			Union of Confidence Interval estimations	
Dep Var	γ	Coeff. in tab 9	Min 90% CI	Max 90% CI
Rank Correlation Lifetime Wage VAPW	0.084	2.752**	0.225	4.725
	(0.260)	(1.200)		
Rank Correlation AKM worker FE VAPW	-0.355**	2.866**	0.901	8.361
	(0.174)	(1.195)		
Strength Matching Lifetime Wage VAPW	0.184	2.280**	-0.668	3.868
	(0.197)	(0.966)		
Strength Matching AKM worker FE VAPW	-0.116	2.926**	0.991	5.965
	(0.195)	(1.176)		

Notes: UCI based on γ coefficients from a regression of assortative matching (i.e. rank correlation between worker and firm type) on the IVs. Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table A10: Movers by worker-type across firms of different types.

	# *High-type movers across firms*		# *Low-type movers across firms*	
year	from *low* to *high* type firm	from *high* to *low* type firm	from *high* to *low* type firm	from *low* to *high* type firm
1996	52	64	66	48
1997	61	28	32	58
1998	108	38	41	109
1999	240	72	77	204
2000	99	35	52	57
2001	56	45	31	48
2002	122	99	87	65
2003	187	124	151	109
2004	146	137	98	89
2005	106	239	155	128

Notes: The table considers only movers with unemployment spell of max one year. High (low) type firms are firms with value added per worker above (below) the median.

Table A11: Immigrant share, assortative matching and the cost of screening.

Dep Var:	*Rank Correlation*		*Strength PAM*	
	(1)	(2)	(3)	(4)
	Panel a: screening cost based on recruiters/HR ratio.			
Immi Sh.	2.432***	1.138*	3.117**	4.042**
	(0.818)	(0.673)	(1.466)	(1.631)
Immi Sh. × Cost screen. (recruiters/HR)	-0.241***	-0.372***	-0.219*	-0.015
	(0.081)	(0.080)	(0.118)	(0.128)
Observations	14,059	14,059	14,059	14,059
First stage coeff. immi share	0.119***			
First stage coeff. interaction	0.391***			
Joint F-stat	11.05			
	Panel b: screening cost based on time to recruit.			
Immi Sh.	2.424***	1.030	3.065**	4.050**
	(0.817)	(0.671)	(1.463)	(1.632)
Immi Sh. × Cost screen. (time recruit)	-0.216***	-0.170**	-0.122	-0.028
	(0.080)	(0.076)	(0.119)	(0.119)
Observations	14,059	14,059	14,059	14,059
First stage coeff. immi share	0.119***			
First stage coeff. interaction	0.390***			
Joint F-stat	11.05			
Worker Type	Lifetime wage	AKM	Lifetime wage	AKM
District FE	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes
Sector-Year FE	yes	yes	yes	yes

Notes: Dependent variables are respectively the rank correlation between worker and firm type, and the strength of positive assortative matching in each district-sector-year. Dependent variables are built at district-sector-year level. Immigrant share and control variables are at district-year level. District-year specific controls are: (i) number of native workers in the district, (ii) concentration of firms and the (iii) share of skilled workers in the districts. Firm type approximated by value added per worker. The lifetime conditioned wage is the average wage earned by the worker over his/hers observed career (period 1995-2005). Worker's wage always purged by experience effect (age), seasonality (year fixed effects) and sector specificities (sector fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

B A model of screening and skill dispersion (For Online Publication)

This section develops a simple model to illustrate the incentives generated by the presence of immigrants with higher dispersion of skills relative to natives. The model does not develop fully a case with several regions. It simply looks at one local labor market with firms and workers of different types and illustrates how the dispersion of workers' skill affects the screening behavior of firms and hence matching with workers. The propositions are derived as comparative statics between individual markets with different characteristics in the distribution of workers' skills. The key intuition formalized in the model is that firms will be more likely to pay a fixed screening cost and improve their probability of matching assortatively when more immigrants are in the labor markets, as the latter group exhibits larger dispersion of skills. In particular, if immigrants generate more dispersion of quality at the top of the distribution (i.e. high quality immigrants are of higher quality than natives) high quality firms will have more incentives to screen and this will generate assortative matching at least for high quality firms. Even if immigrants can be distinguished from natives, if the cost of screening is fixed, their presence increases the probability for firms, especially high quality ones, screening for quality of ***all*** workers.

B.1 Model with two types of firms and workers

Consider an economy with labor force of unit mass, in which workers come in two different quality levels (types) with productivity equal to $\underline{\theta_w}$, for the low productivity ones, and $\overline{\theta_w}$, for the high productivity group, where $1 < \underline{\theta_w} < \overline{\theta_w}$. We assume that both groups have the same size so that each quality level of worker, denoted as $\mu \in \{\underline{\theta_w}, \overline{\theta_w}\}$, comprises 1/2 of the total labor force. We also assume that while all workers can observe their quality (type), firms cannot observe the specific quality of the worker. Therefore, $\frac{1}{2}(\underline{\theta_w} - \overline{\theta_w})$ is the standard deviation of the expected quality of workers in a group, from the firm's perspective. There is also a unit mass of firms with average quality (productivity) $\frac{1}{2}(\underline{\theta_f} + \overline{\theta_f})$ and among them half have relatively high quality $\overline{\theta_f}$ and half of them have relatively low quality $\underline{\theta_f}$, with both values larger than one. This generates a distribution of firms over the quality levels $\phi = [\underline{\theta_f}, \overline{\theta_f}]$, with half of the firms in each group.

Each firm j matches with one worker i [53] and produces surplus (value added) according to the following production function, in which the quality of firms and workers are complementary in a multiplicative way:

$$Y_{i,j} = (\mu_i * \phi_j) \tag{7}$$

This expression is a special case that captures the complementarity between the quality of firm and workers and the super-modularity of production.[54] Once the match has taken place and production

[53] In a recent paper Eeckhout & Kircher (2018) show that assortative matching happens across firms of different size (i.e. when the firm matches with many workers). In their model the firms choose both the quality and the quantity (size) of their workforce. In this case, positive assortative matching not only depends on the degree of complementarity between types, but also on the complementarity between types and quantity.

[54] With this property high-quality workers are paid more, in general, but are particularly valuable to high quality firms (as in Kremer 1993).

begins, the surplus is split equally between wage of the worker and profit of the firm, so that the wage of worker i is:[55]

$$W_i = \frac{(\mu_i * \phi_j)}{2} \tag{8}$$

and the profit of firm j is:

$$\Pi_j = \frac{(\mu_i * \phi_j)}{2} \tag{9}$$

Notice that in expression (8) wages are log-linear in the quality of the firm and in the quality of the worker, just as the AKM decomposition requires. We assume that firms have imperfect information and cannot distinguish the identity of high- and low-quality workers without screening them. Firms, however, can pay an ex-ante fixed cost, K, and set-up a screening mechanism after which they are able to observe worker quality and match in every period with the preferred type. For the moment we assume that this screening cost is equal for each firm and is a fixed cost, so once paid it allows a firm to observe the quality of any matched worker. The fixed cost nature of screening is qualitatively supported by the fact that recruitment over total human resources workers ratio decreases with the firm size. See Figure B1.

The incentives to pay the screening costs are higher for the high-quality firms as they have a larger marginal profit from matching with high-quality workers, due to the convexity of production and complementarity between high-quality firms and high-quality workers. Hence, if the screening cost is below a certain threshold, the high-quality firms (those with quality $\overline{\theta_f}$) will pay the screening cost and will match with high-quality workers, leaving low-quality workers to low-quality firms. In this simple model with only two-types, this implies perfect positive assortative matching. However, if the screening cost, to be paid ex-ante,[56] is above the threshold, high quality firms will not pay it and we assume there will be random matching with the workers. The expected profit of the high-quality firms when paying the fixed screening cost K and certainly matching with the high quality workers is:

$$E(\pi_S) = \frac{(\overline{\theta_f})(\overline{\theta_w})}{2} - K \tag{10}$$

while the expected profit when they do not screen and thus match randomly with workers is:

$$E(\pi_R) = \frac{0.5(\overline{\theta_f})(\overline{\theta_w}) + 0.5(\overline{\theta_f})(\underline{\theta_w})}{2} \tag{11}$$

Therefore, high quality firms will pay the screening cost if $E(\pi_S) > E(\pi_R)$, which implies that the screening cost should be lower than the following positive threshold:

$$K < \frac{0.5(\overline{\theta_f})(\overline{\theta_w} - \underline{\theta_w})}{2} \tag{12}$$

If this condition is satisfied then the high-quality firms will pay the screening cost and match with all the high-quality workers, leaving the unmatched low-quality workers to the low-quality firms. Hence, if the condition above is satisfied, full assortative matching prevails in this model, meaning that high-

[55]The surplus can be split in any proportion between firm and worker. We choose 1/2 for illustrative purposes.

[56]The screening cost can be thought also as a period of trial in which the high-quality firm learns the type of workers and then starts production only if the worker is high-quality.

quality firms will match with high-quality workers only, and low-quality firms with low-quality workers only. Notice that in this model what matters is the screening cost for the high-quality firms. Low quality firms, even if they screen, will not be able to attract high quality workers as they would pay lower wages. Hence, what matters is whether high-productivity firms decide to screen or to match randomly. If the cost of screening K is different between high- and low-productivity firms, then it is the screening cost of high-productivity firms that determines whether these firms screen of match randomly. So in equilibrium high-productivity firms screen and hire all high-quality workers and pay them higher salary, while the low-quality firms will match with the remaining low-quality workers. Two simple implications derive from the model sketched above:

1. If the cost of screening is equal across high-productivity firms in a labor market, then the probability of observing high-quality firms screening for high-quality workers in that market is decreasing in the threshold value of K, and increases with the standard deviation of workers' quality $0.5(\overline{\theta_w} - \underline{\theta_w})$.

2. For common screening costs, the probability of screening and matching assortatively will be higher if high productive firms have higher average productivity, $\overline{\theta_f}$.

Notice that the incentive of the high quality firm to do screening only depends on the dispersion of worker's quality, not on their average quality. Hence any change in the labor force increasing its quality dispersion will create incentives for high quality firms to do screening, which will increase their probability of assortative matching.

B.2 The model with immigrants

We now introduce immigrants to the model. Immigrants are assumed to have a larger standard deviation of types (uncertainty) but the similar average quality of native workers. Immigrants come from different backgrounds, so their adjustment to local labor markets can be very different. In general, their background and the quality of their education and working experience can be very different. Overall, as they come from different countries, they are a more heterogeneous group than natives in their quality, even controlling for their observable characteristics. We can think of this as a result of their country of origin diversity, but also as a result of the different selection that they have in different countries (positive from some countries and negative from others, as predicted by Borjas 1987). The higher quality dispersion of immigrants is shown in the data in section 4.1.2. A realistic way to capture this in the model, and reflecting the statistics reported in section 4.1.2 and Table 4 is to think that immigrants have higher "top quality" and lower "bottom quality" workers. In our simple model, this implies that: $(\overline{\theta_w^I} - \underline{\theta_w^I}) > (\overline{\theta_w^N} - \underline{\theta_w^N})$ where "I" indicates immigrants and "N" native workers. This immediately implies that in a population of all immigrants, the probability of screening by the high-quality firms is higher than in a population of all natives, and therefore assortative matching is more likely for a given screening cost.

When the population in a labor market is a mixture of the two groups (I and N), and assuming that their average type is the same, the standard deviation of the population is a linear combination of those of the two groups expressed as: $\left[(\overline{\theta_w^I} - \underline{\theta_w^I}) * sh_I + (\overline{\theta_w^N} - \underline{\theta_w^N}) * (1 - sh_I)\right]$, where sh_I is the share of immigrants in the total population of workers. Then, the condition for high-quality firms to perform screening is:

$$K < \frac{0.5(\overline{\theta_f})\left[(\overline{\theta_w^I} - \underline{\theta_w^I}) * sh_I + (\overline{\theta_w^N} - \underline{\theta_w^N}) * (1 - sh_I)\right]}{2} \tag{13}$$

In this case the probability of screening and assortative matching increases in the share of immigrant workers sh_I as long as the standard deviation of immigrants' quality is larger than that of natives' quality.[57] This is the key implication that we test in the empirical part of the paper, namely:

Proposition 1 *For a given cost of screening, markets with a larger share of immigrants have a stronger incentive to perform screening which will result in PAM between workers and firms.*

A corollary of (*Proposition 1*), based on equation (13), is that the probability of PAM is larger when the dispersion of immigrant quality, $(\overline{\theta_w^I} - \underline{\theta_w^I})$, is larger.

Corollary 1.1 *The e ect of immigrant share on the incentive to perform screening and on improved PAM between workers and firms is magnified in local labor markets where immigrant quality is more dispersed.*

Another important implication of the model above is that average value-added (surplus) and hence average wage and profits of firms will be larger in markets where PAM occurs. Hence, the latter will be positively associated with the share of immigrants, if PAM is the main channel for the local impact of immigrants. This is easily proven by writing the difference between average surplus with PAM ($E(S_{PAM})$) and average surplus with random matching for firms ($E(S_R)$). This difference is:

$$E(S_{PAM}) - E(S_R) = \frac{1}{2}[(\overline{\theta_f \theta_w} + \underline{\theta_f \theta_w}) - (\underline{\theta_f}\overline{\theta_w} + \overline{\theta_f}(\underline{\theta_w})] = \frac{1}{2}(\overline{\theta_f} - \underline{\theta_f})(\overline{\theta_w} - \underline{\theta_w}) > 0 \tag{14}$$

The expression is always larger than 0 and it depends positively on the dispersion of the firm's quality and of the worker's quality. The "complementarity" (multiplicative) between the quality of each partner in the match, implies that assortative matching will generate larger average surplus than random matching. As workers and firms split the surplus (see equations 8 and 9), the inequality in the expected surplus in equation (14) will carry over also to firms' average profit which equals 1/2 of the surplus and, because of condition (12) is larger even after paying the screening costs. So the final implication of our simple model is that:

Proposition 2 *Local markets with larger shares of immigrants (i.e. wider dispersion in unknown types) have higher average firm profits and larger average wages.*

[57] Given equation (13) we cannot exclude *a priori* the circumstance in which immigrants affect the probability of screening (and then the strength of PAM) through an indirect effect on the average productivity of firms θ_f. The empirical evidence proposed in section 7 aims at isolating the direct effect of migration through the increased dispersion of worker type ε_I.

This proposition is also tested in the empirical section of the paper. Additionally, PAM will increase the standard deviation of workers' wages and of firms' profits as the match distribution will be concentrated on the extreme outcomes, $(\overline{\theta_f \theta_w})$ and $(\underline{\theta_f}\underline{\theta_w})$, rather than on the intermediate ones, $(\overline{\theta_f}\underline{\theta_w}$ and $(\underline{\theta_f}\overline{\theta_w})$. Hence:

Proposition 3 *A higher share of immigrants (i.e. wider dispersion in unknown types) will be associated with higher wage- and profit-dispersion.*

Notice that if we consider the screening cost as paid ex-ante, and mainly a fixed cost (not varying much with how many people are screened) once firms paid the cost K, they will screen ***all*** workers. Hence, if it makes sense to pay the screening cost for the aggregate labor force, they will also screen natives and generate assortative matching with them. Thus, the presence of immigrants will also increase the assortative matching of natives and therefore their average wages in the region. This positive impact on the matching of natives takes place only if there is initial uncertainty about the quality of natives. If firms can perfectly observe the quality of natives without screening, then the "spillovers" from screening on better matching native workers does not occur. The empirical evidence provided in Table 15 supports the presence of uncertainty about the quality of native workers, and therefore a migration-induced PAM effect for native workers.

B.3 Model with many types of firms and workers and different screening costs

Let us now consider an economy similar to the one described in the previous section, but with $2N$ types of firms and workers characterized by different productivity levels. To make notation easier we consider a symmetric distribution of types around an average quality, θ_w , so that workers' productivity can be any of the following $2N$ levels $[\theta_w - \epsilon, \theta_w - \frac{N-1}{N}\epsilon, ...\theta_w - \frac{\epsilon}{N}, \theta_w + \frac{\epsilon}{N}...\theta_w + \frac{N-1}{N}\epsilon, \theta_w + \epsilon]$ so that one can rank their quality in increasing order from $i = -N$ to $i = N$ and ϵ is a measure of overall quality dispersion. Similarly, assume that there are $2N$ groups of firms of productivity equal to $[\theta_f - x, \theta_f - \frac{N-1}{N}x, ...\theta_f - \frac{x}{N}, \theta_f + \frac{x}{N}...\theta_f + \frac{N-1}{N}x, \theta_f + x]$ so that we can rank their quality in increasing order from $i = -N$ to $i = N$ and x is a measure of overall quality dispersion for firms. Let's also assume that each group of firms, indexed by quality index $j = -N, -N+1, ... -1, +1, N-1, N$ has, potentially different, screening cost K_j. The firms at the top level quality ($j = N$), with productivity equal to $\theta_f + x$ are those with the strongest incentives to screen. These firms will screen if the generated profit from paying the screening cost and assortatively matching with workers of top quality group $(\theta_w + \epsilon)$ is larger than than matching randomly and not paying the screening cost. Namely:

$$(\theta_f + x)(\theta_w + \epsilon) - K_N \geq \frac{1}{2N}(\theta_f + x)\sum_{j=-N}^{+N}\left(\theta_w + \frac{\epsilon}{N}j\right) \tag{15}$$

This inequality, after isolating K_N and simplifying the terms in the symmetric summation, reduces to:

$$K_N \leq (\epsilon)(\theta_f + x) \tag{16}$$

The expression in square brackets in the inequality (16) above is linear and increasing in ϵ, in x, and in θ_f. Therefore, for a given screening cost, the higher is ϵ (the dispersion of workers' quality types), the higher is x (which captures the dispersion of firm productivity), and the higher is average firm productivity θ_f, the more likely the top-quality group of firms will be to screen. If the inequality is satisfied, the top firm types do the screening, match with the top quality workers, and the other $2N-1$ firm types are left to decide whether to screen or to randomly match with the remaining $2N-1$ workers types. In general, for a firm of quality type M with costs of screening K_M, screening will be optimal if:

$$K_M \leq \left[\frac{M}{N}\epsilon - \frac{1}{N+M-1}\sum_{j=-N}^{M-1}\left(\frac{\epsilon}{N}j\right)\right](\theta_f + \frac{M}{N}x) \tag{17}$$

The expression in square brackets in the inequality (17) above is linear and increasing in M. Therefore as we move to lower quality firms the incentive to do screening decreases monotonically. This has the following two implications that generalize the basic results from a two-type model to this multi-type model:

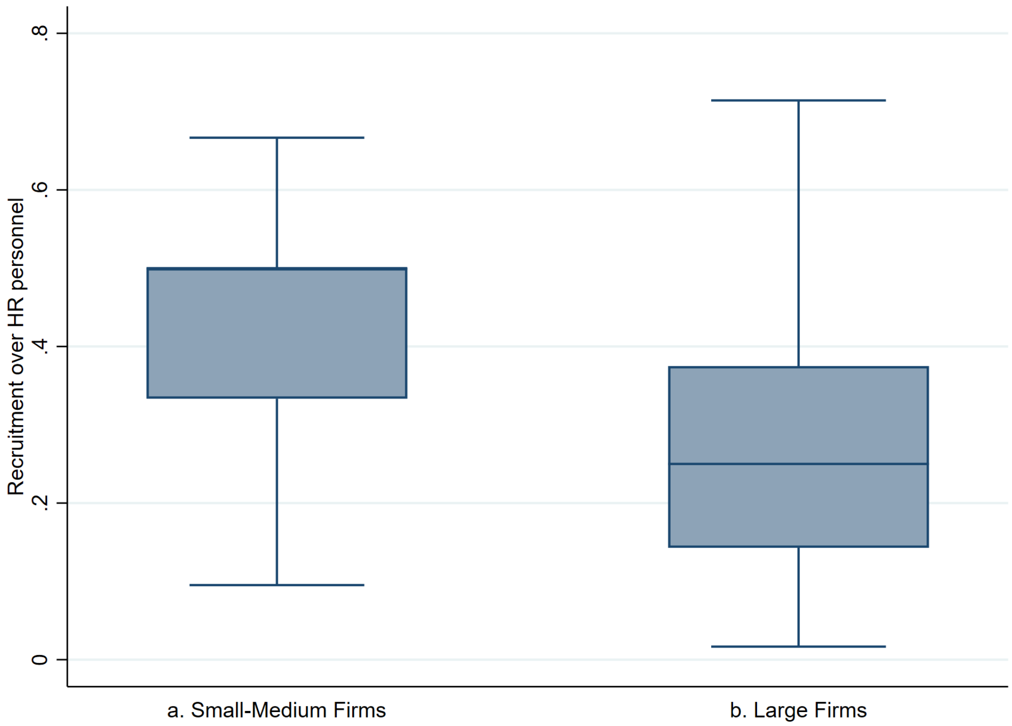
1. For a cost of screening that is constant among firm types or declining with quality, M, there will be a "marginal quality group" such that all groups of higher quality pay the screening cost and match assortatively, and those with lower quality do not screen and match randomly. This is an immediate consequence of the fact that the threshold for screening in (17) is increasing in M. For screening costs that are excessively high, no firm will screen; for very low screening costs, all firms will screen.

2. For a given schedule of screening costs, which can be a non increasing function of M, the share of firms doing screening (and therefore the intensity of assortative matching) increases in the dispersion of quality types of workers. The share of firms doing assortative matching will always be positively selected in terms of quality.

The key insight of the multi-type model, confirming the two-type model, is that an increased dispersion in quality of workers leads to an increased share of firms doing assortative matching, and this in turn increases average profits and average wages.

While this model is extremely simplified, the basic intuition that a larger dispersion of worker quality makes screening more profitable for high-quality firms and increases the share of positive assortative matches (and therefore the average wages and productivity when firm and worker quality are complementary) is a very robust implication of a super-modular production function. It holds for 2 and for N quality groups, and as N becomes larger this can approximate a continuum of quality levels.

Figure B1: Ratio between recruitment and human resources workers by firm size.



Source: Authors calculations on DARES (French Ministry of Labor) data. *Note*: Survey based data on the recruitment process of firms in 2005.

C AKM decomposition orthogonality conditions and results (For Online Publication)

As explained in section 3.2, we use worker fixed effects from AKM decomposition as an alternative proxy for worker type (robustness check). To this end, we employ longitudinal matched employer-employee data (DADS *panel*) to estimate the standard mincerian wage equation as in Abowd et al. (1999):

$$ln(wage)_{i,t} = \alpha_i + \Phi_{\mathbf{J}(i,t)} + X_{i,t} + r_{i,t} \tag{18}$$

where $ln(wage)_{i,t}$ is the log annual wage of worker i at time t; $\Phi_{\mathbf{J}(i,t)}$ is a firm fixed effects (representing the firm specific component in standard additive wage setting equation), α_i is a set of worker fixed effects that we use as an alternative proxy for the worker type and $X_{i,t}$ is a set of worker-time controls capturing life-cycle and other aggregate factors that affect the wage of workers with specific characteristics (i.e. age) in a given geographic area (i.e. Ile di France). Namely, the set of observable characteristics ($X_{i,t}$) includes the quartic polynomial in age, the *Ile-de-France* dummy, and a gender dummy interacted with the quartic polynomial in age, Ile-de-France and year dummies. The error term $r_{i,t}$ consists of three separate random effects: (i) a match component $\eta_{i\mathbf{J}(i,t)}$ representing the idiosyncratic wage surplus earned by the worker i when matches a specific firm j, (ii) a unit root component ζ_{it} representing the time-varying component of the individual-specific earning power (such as human capital accumulation, health shocks, etc), and (iii) the pure idiosyncratic individual wage component ϵ_{it}.

Limited mobility bias. The correct identification of firm and worker fixed effects in equation (18) relies on a sufficient degree of mobility of workers across firms. This may represent an important concern in less populated districts. So, as a first way of reducing the limited mobility bias concern, we exclude from the AKM estimation in eq.(18) districts with total employment below the 25^{th} percentile. Results using assortative matching measures based on AKM fixed effects that exclude small districts are reported in columns (1) and (4) of Table C1. Alternatively, using k-means cluster analysis, we group firms with similar wage structure into 15 clusters and include *cluster* rather than *firm* fixed effects in eq. (18). Quartiles and deciles of firms' wage distribution are (respectively) used to perform the k-means cluster analysis. The grouping of firms into clusters ensures that there is more worker mobility between clusters than individual firms, and mitigates the limited mobility bias concern. Results using this alternative approach to obtain AKM fixed effects are reported in column (2), (3), (5) and (6) of Table C1. A similar approach is used in Dauth et al. (2022).

Orthogonality condition. The correct identification of the OLS coefficients for α_i, $\Phi_{\mathbf{J}(i,t)}$ and $X_{i,t}$ bases on their orthogonality with respect the error component $r_{i,t}$. The orthogonality between individual fixed effects, time-varying covariates and the error component is standard and widely recognized as valid (see Card et al. 2013).[58] However, the orthogonality condition between the firm fixed effect and the three components of the error term must be discussed and verified. In other words, for a proper identification of equation (18) we need exogenous mobility.

[58]The orthogonality between worker fixed effects and the error component $r_{i,t}$ follows from the assumption that $\eta_{i\mathbf{J}(i,t)}$, ζ_{it} and ϵ_{it} have zero mean.

To this end, we follow Card et al. (2013) and perform an event study analysis of the effect of job changes on wages (see section IV.B in Card et al. 2013). This proceeds in four steps. First, for each individual i at time t we calculate the average co-worker wage. Second, for each job changer (or mover) with at least two-year employment spell in the old and new employer we classify the bin (above *vs* below the median) of co-worker wage in old and new employer. Third, each job changer is assigned to one of the 4 possibles job transitions (from one of the two bins in co-worker wage of the old employer, to one of the two bins of the new employer). Finally, we calculate the average observed wage of job-changers for each specific job transition before and after the job change. Figure C1 shows the results of this exercise for job transitions for workers leaving jobs in high- and low-coworker wage firms (i.e. jobs in firms with above-the-median and below-the-median paid coworkers). The first reassuring feature of Figure C1 is the approximate symmetry in the patter of wage for workers that move between high- and low-coworker wage bins. The gains associated with transitioning from a low- to a high-coworker wage firm are roughly equal to the losses associated to the opposite transition. Also, workers that move between firms belonging to the same bin in coworker wage experience a small change in their wage, indicating a small general mobility premium for movers. This suggests that the choice to work for a specific firm does not depend on the expected surplus component of the worker-firm match (allowing us to not explicitly include worker-firm match fixed effects in the AKM decomposition). In other words, we do not observe sorting of workers based on the match component. This qualitative evidence supports the validity of the the simple model with additive worker and firm effect at the base of the AKM decomposition.

An additional validity check for the AKM decomposition (and the underlying additive wage model) is testing the improvement in the fit of the data after explicitly including match fixed effects in the estimation of equation (18) as done in Card et al. (2013) and Dauth et al. (2022). Indeed, if the match effect is important in determining the wage of workers, then a fully saturated model including worker-firm match fixed effects would fit the data much better than a simple additive model. Consistently with the additive nature of equation (18), we find that the inclusion of job-specific fixed effects only marginally improves the R-square of the AKM estimation: from 0.952 to 0.954.

To obtain unbiased estimations of worker and firm effects from AKM decomposition, we need to check that job moves do not depend on drift in worker's expected wage (included in the residual term of the additive model in AKM). The absence of any substantial trend in wage before the move towards a better firms (with the exception of the high-to-high transition showing some trend in wage over the transition), suggests the absence of a learning process (drift) that may bias the estimations. Finally, unbiased estimation of worker and firm effects also requires that the transitory error component of the additive model is not associated with systematic movements across firms of different quartiles. The fact that pre-move wage dynamics are almost flat, and the symmetry in the wage pattern across firms of different quartiles reduce any concern of job mobility related to transitory wage fluctuations.

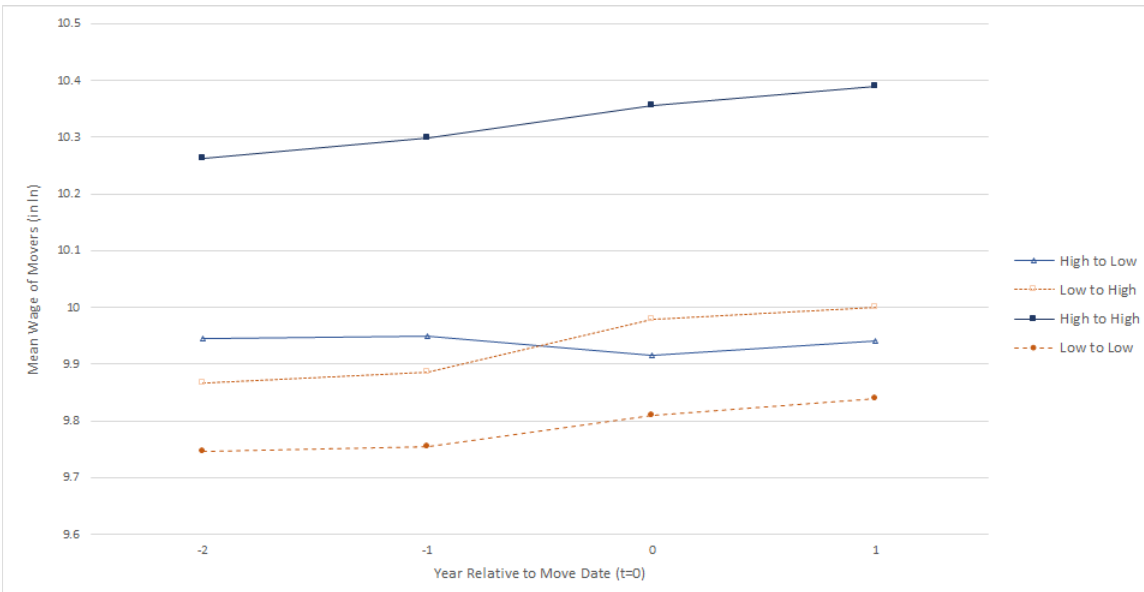
Finally, in Table C2 we report some descriptive statistics of the parameters obtained from the AKM decomposition computed over the period 1995-2005. We have approximately 2 million worker-firm observations, and the average (ln) wage is equal to 9.8 with a standard deviation equal to 0.46. Reassuringly, our results from AKM decomposition are in line with previous studies. In line with results in Table III in Card et al. (2013) and Dauth et al. (2022), we obtain a standard deviation of worker effects larger than firm effects. Also, in line with Dauth et al. (2022) in their 1985-1991 panel of German firms and workers, we obtain (small) negative correlation between worker and firm fixed effects.

Table C1: Robustness check for limited mobility bias in AKM estimations.

Dep Var:	*Rank Correlation*			*Strength PAM*		
	(1)	(2)	(3)	(4)	(5)	(6)
Immi Share	2.618**	1.152	1.351	1.682*	2.356**	2.305**
	(1.144)	(0.971)	(0.972)	(0.977)	(1.050)	(1.045)
Worker Type	AKM no small districts	AKM cluster qtl wage	AKM cluster dec wage	AKM no small districts	AKM cluster qtl wage	AKM cluster dec wage
District FE	yes	yes	yes	yes	yes	yes
Region-Year FE	yes	yes	yes	yes	yes	yes
District-Year controls	yes	yes	yes	yes	yes	yes
Observations	781	1,012	1,012	781	1,012	1,012
First stage coeff.	0.131***	0.121***	0.121***	0.131***	0.121***	0.121***
F-stat	10.96	16.64	16.64	10.96	16.64	16.64

Notes: Dependent variables are respectively the rank correlation between worker and firm type and the strength of positive assortative matching in each district-year. Worker type based on AKM fixed effects measures. Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Figure C1: Mean wage of job changers by bins of coworkers wage at origin and destination firm.



Source: Authors calculations on DADS and Ficus/Fare data. *Note*: The figure shows wage levels of job movers in the period 1995-2005 at old firm two years prior to the move (t=-2 and t=-1); and the wage levels at the new firm in the year of the move (t=0) and the year after (t=1). These have been obtained by average wage of movers classified by bins of co-worker wages in the old and new firm.

Table C2: Estimation results for AKM model.

	Period 1995-2005
Worker and firm parameter	
Number worker effects	389962
Number firm fixed effets	112579
Summary of parameter estimates	
Mean worker effects (across worker-year obs)	-0.000
Mean firm effects (across worker-year obs)	-0.076
Median worker effects (across worker-year obs)	-0.173
Median firm effects (across worker-year obs)	-0.039
Std. Dev. worker effects (across worker-year obs)	0.814
Std. Dev. firm effects (across worker-year obs)	0.198
Correlation (worker FE, firm FE)	-0.202
R-squared	0.952
Other statistics	
Average log wage	9.861
Std dev log wage	0.457
Sample size	1941645

D Rotemberg weights and validity tests (For Online Publication)

The identification of the shift-share IV adopted here bases on the exogeneity of the initial shares of migrants used to allocate origin-specific and time variant migration inflows (Goldsmith-Pinkham et al. 2020). This section aims at strengthening the credibility of our empirical design by applying some specification tests on the initial (origin-specific) migrants shares that have the highest impact on our baseline 2SLS results. Namely, we calculate the Rotemberg weights for each origin-specific share of immigrants in 1982 and apply the specification validity tests prescribed by Goldsmith-Pinkham et al. (2020) for the top-5 origins in terms of Rotemberg weights. Such weights depend on the covariance between the fitted value of each origin-specific migration share on the endogenous variable and the endogenous variable itself, and intuitively tell how sensitive is the overidentified estimate of the coefficient of interest ($Immmi\ sh$ in our setting) to the mispecification in any of the origin-specific migrant share. In practice, such weights reveal which specific migrants communities (in 1982) have more importance in the overall 2SLS estimate. So testing the specification validity for the sub-sample of origin-specific shares that affect the most the overall 2SLS estimation will reassure on the general validity of our estimations.

In line with the LFS data in 1982 used to build the origin-specific shares of migrants in 1982, we have 22 origins o.[59] Panel 2 of Table D1 shows the top-5 origin countries in terms of Rotemberg weights $\hat{\alpha}_k$ (we closely follow the notation in Goldsmith-Pinkham et al. (2020) and use subscript k to indicate the origin country). The top-origin in terms of weights is the "Other Countries n.e.c." (covering mainly South American and other Asian countries) which receives itself almost half of the weight ($\hat{\alpha}_k = 0.58$). The top-5 countries (in order of Rotemberg weights: Other Countries n.e.c., Other African countries, Portugal, Ex-Yugoslavian countries, Algeria) account for almost the 80% of the overall weight. The large weight for the macro origin "Other Countries n.e.c." is not surprising as it includes big migrants communities in France (such as the Chinese, the Indian and the South American ones) and mimic the big Rotemberg weigth associated to Mexico obtained by Goldsmith-Pinkham et al. (2020) for the US immigration example. Also, in panel 1 of Table D1 we show that the correlation between weights and the migrants inflows (g_k in Table D1) is very high (0.96), suggesting that weights are considerably explained by shocks (another feature in common with the enclave IV applied to the US case in Goldsmith-Pinkham et al. 2020).

With the list of top-5 migrants origins in terms of Rotemberg weights we can test the plausibility of our identifying assumption. First, in Table D2 we show the correlation between initial migration shares across districts for each of the top-5 origins and the average district's wage in 1982 (we only have LFS data for the year 1982, and so very limited choices in terms of variables approximating the economic performance of districts in 1982). The absence of correlation (with the exception of the Portuguese community) suggests that the initial settlement of immigrants (by origin) across French districts does not reflect the *level* of the economic performance of the local labor market.[60] Second,

[59] The 22 origins in LFS data are: Algeria, Tunisia, Morocco, Other African countries, Vietnam-Laos-Cambodia, Italy, Germany, Belgium, Netherlands, Luxembourg, Ireland, Denmark, UK, Greece, Spain, Portugal, Switzerland, Austria, Poland, Ex-Yugoslavia, Turkey, and Other Countries n.e.c.

[60] For a proper correlation test, as prescribed by Goldsmith-Pinkham et al. (2020) we should have correlated initial migrants share with the PAM measures in 1982. These are unfortunately not available for the year 1982 so we used

we replicate the pre-trend exercise as presented in Goldsmith-Pinkham et al. (2020) for each of the top-5 origins highlighted here. Namely, we regress respectively our four measures of strength of PAM in the starting year (1995) on the origin-specific share of immigrants in 1982 (including the same set of controls X_d included in equation 2 for the year in 1995). Results reported in Table D3 show that the variation in the initial origin-specific share of immigrants did not predict statistically or economically larger strength of PAM across districts (no matter the measure of PAM adopted). This, combined with our baseline results, suggests that there has been a shock in the share of immigrants over the period 1995-2005 that improved the strength of PAM.

Table D1: Summary of the Rotemberg weights

Panel I: Correlations					
	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	$\hat{F}_k$	$Var(z_k)$
$\hat{\alpha}_k$	1				
g_k	0.957	1			
$\hat{\beta}_k$	0.078	0.042	1		
$\hat{F}_k$	0.202	0.210	0.062	1	
$Var(z_k)$	0.049	-0.121	0.049	-0.302	1
Panel II: Top-5 Rotemberg weight origins					
	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$		
Other Countries n.e.c.	0.577	2.07e+06	0.781		
Other African countries	0.074	6.99e+05	1.635		
Portugal	0.048	5.27e+05	0.658		
Ex-Yugoslavia	0.046	1.85e+05	0.000		
Algeria	0.035	4.02e+05	2.126		
Panel III: Variation across years in $\hat{\alpha}_k$					
	Sum	Mean			
1995	0.029	0.001			
2000	0.094	0.004			
2005	0.134	0.006			

Notes: This table reports statistics about the Rotemberg weights obtained following the procedure described in Goldsmith-Pinkham et al. (2020) and adapted to our specific empirical framework. Panel I report the correlations between weights ($\hat{\alpha}_k$), the French inflow of migrants from a given origin k, (g_k), the just-identified point estimate $\hat{\beta}_k$, the first stage F-stat ($\hat{F}_k$), and the variation in the origin country shares across districts ($Var(z_k)$). Panel II report the top-5 origin countries in terms of Rotemberg weights. Panel III reports the variation in the weights across years.

average wage as a proxy for the economic performance of the local labor market.

Table D2: Origins specific shares and labor market characteristic in 1982.

Dep Var:	*Share of immigrants in 1982 originating from*				
	Other countries n.e.c.	Other African countries	Portugal	Ex-Yugoslavia	Algeria
Avg wage in 1982	-0.003	-0.000	0.005**	0.002	0.004
	(0.009)	(0.004)	(0.002)	(0.006)	(0.004)
Observations	92	92	92	92	92
R-squared	0.391	0.620	0.765	0.348	0.453

Notes: Each column shows the results of a regression of a given (origin-specific) share of immigrants in 1982 on the average wage across districts in 1982 (conditioned on region fixed effects). Robust standard errors in parenthesis. *** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.

Table D3: Pre-trend for high Rotemberg weight origins

Dep Var:	*Share of immigrants in 1982 originating from*				
	Other countries n.e.c.	Other African countries	Portugal	Ex-Yugoslavia	Algeria
Rank Correlation (lifetime wage)	-0.165	0.047	-1.235*	-0.297	-0.328
	(0.164)	(0.417)	(0.718)	(0.191)	(0.413)
Rank Correlation (AKM)	-0.019	0.082	0.607	-0.143	0.564
	(0.207)	(0.403)	(1.035)	(0.233)	(0.430)
Strength of PAM (lifetime wage)	-0.087	0.289	-0.226	-0.165	-0.190
	(0.165)	(0.315)	(0.914)	(0.173)	(0.330)
Strength of PAM (AKM)	0.033	0.080	0.764	-0.032	0.662
	(0.182)	(0.376)	(0.922)	(0.227)	(0.457)

Notes: Each entry of the table reports the results of a regression specification having a proxy for the strength of PAM in 1995 as dependent variable and the 1982 share of immigrant for a given origin country. The same set of control as in eq. 2, and region fixed effects are included in such specifications. Robust standard errors in parenthesis.*** $p < 0,01$; ** $p < 0,05$; * $p < 0,1$.