How Migration Reshapes Job Tasks for Native Workers in Italy

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Abstract

Using detailed employer–employee data from the Italian Institute of Social Security (INPS) for the years 2013–2019, we study how changes in the local supply of migrant workers affect the tasks performed by Italian workers. We measure how routine different jobs are across 796 five-digit ISCO occupational groups using newly data from the Inapp–Istat Survey on Italian Occupations (ICP), an O*NET-type dataset.

Exploiting differences across local labor markets, we show that a higher share of migrant leads native workers to adjust their occupations. Less-educated natives tend to move into less routine jobs, and workers at all education levels reduce the time they spend on manual tasks. These patterns are similar for men and women. The effects are stronger among workers who switch employers within their local labor market and are mainly found in more productive firms, which seem better able to benefit from the presence of migrants. The econometric results are robust to several checks and alternative specifications.

1 Introduction

Immigration to OECD countries is an increasingly important phenomenon (OECD, 2017). During the last years, a large literature started to investigate the effects of immigration on labor market outcomes of native-born workers in rich receiving countries, with a special focus on the impact of immigration on natives' wages and employment (e.g., Ottaviano and Peri (2012) for the US; D'Amuri et al. (2010) for Germany; Manacorda et al. (2012) for the UK). Generally, the literature shows that what matters in determining the effect of immigration on natives' wages is the elasticity of substitution between natives and migrants, within comparable skill groups. One element that is often commented upon is the role of recent immigration waves in worsening the labour market status of natives, especially the low skilled ones. The literature is large and so far has not reached a consensus regarding the degree of substitutability between natives and migrants in the production function and therefore the impact of immigrants on natives' wages. However, it is generally shown that for most groups of native workers, the impact of immigration on wages is low (see for instance Docquier et al. (2014) who simulate the impact of immigration on natives' employment and wages, across a wide number of OECD countries, and under different elasticity of substitution assumptions within comparable skill groups) with some exceptions for the US (e.g., Borjas (2006)). Although the wage effect of immigration may be negligible, Dustmann et al. (2013) estimate the impact of overall immigration along the native wage distribution in UK. They find that immigration decreases the wage of native workers at the bottom of the wage distribution (below the 20th percentile) and increases the one of those that belong to the upper tail of the distribution (above the 40th percentile). A related but less explored line of research asks whether natives respond to immigration not only through wages, but also through occupational and task reallocation. If immigrants and natives are imperfect substitutes, native workers may specialize in tasks in which they have a comparative advantage, thereby attenuating potential wage losses. In this case, immigration may induce natives to move toward more complex tasks or more highly ranked occupations, rather than simply displacing them from employment. This mechanism may differ across the education distribution, but it may be relevant for both low- and high-skilled workers.

Existing evidence is consistent with this view. Using data for US states from 1960 to 2000, Peri and Sparber (2009) show that less educated immigrants specialize in manual tasks, while less educated natives shift toward occupations more intensive in communication tasks. In a companion paper, Peri and Sparber (2011) show that highly educated native workers also respond to immigration by moving toward occupations with greater communication and interactive content, while highly educated immigrants specialize relatively more in analytical and quantitative tasks. Evidence outside the US points in the same direction. Cattaneo et al. (2015), using the European Community Household Panel (ECHP) matched with ELFS data for 11 EU-15 countries, find that immigrant inflows increase the probability that natives move to occupations with higher wages, education requirements, and social status. Foged and Peri (2016), using Danish longitudinal data, show that an increase in the supply of low-skilled refugees pushes less educated natives, especially the young and those with low tenure, toward less manual-intensive and more complex occupations.

This paper contributes to this literature by studying the effect of immigration on the task content of native employment in Italy. Using Italian administrative data, we examine how variation in the share of migrants across local labor markets affects the tasks performed by native workers. We find that in areas more exposed to international migration, native workers are more likely to perform less routine tasks. More specifically, low-skilled workers, and to a lesser extent high-skilled workers, are less likely to be employed in routine and non-routine manual activities and more likely to be employed in non-routine cognitive activities. These effects hold for both men and women and are primarily driven by workers employed in large and highly productive firms. The results are robust to alternative fixed-effect specifications that account for changes in task content within firms, within local labor markets, and across local labor markets. Our identification strategy, based on the historical distribution of migrants across local labor markets, is robust to alternative instruments, and additional tests support the exclusion restriction by showing that current economic shocks are not correlated with the historical settlement pattern of migrants.

The paper makes three related contributions. First, it provides new evidence for a major but still understudied European receiving country. Italy is an especially interesting case for at least two reasons. On the one hand, since the early 1990s it has transformed from a country of emigration into one of Europe's main destinations for labor migrants, with immigration flows largely concentrated in low-skilled occupations. On the other hand, its productive structure differs in important ways from the settings most commonly analyzed in the literature. The Italian economy is characterized by the prevalence of small and medium-sized firms, specialization in medium- and low-technology sectors, relatively weak innovation performance, and marked territorial heterogeneity. These features are likely to shape both firms' demand for tasks and workers' scope for adjustment in response to immigration, making Italy a particularly informative setting in which to study whether immigration induces native workers to move away from routine and manual activities and toward more cognitive tasks.

Second, unlike most of the literature on task specialization, which relies on ONET-based indicators, we measure task content using the INAPP–ISTAT Survey on Italian Occupations, following the approach adopted in Cirillo et al. (2021). This is an important advantage because the survey is built directly on the Italian occupational structure and therefore provides task measures that are better aligned with the institutional and productive features of the Italian labor market. Using country-specific occupational data reduces the measurement problems that arise when US-based ONET information is mapped into a different occupational and institutional context.

Third, we combine this task classification with Italian administrative records rather than standard survey data. This provides large-scale and precise information on workers' employment trajectories, allowing us to observe native workers' occupational allocation over time with broader coverage and less measurement error than is typically possible using survey data. In turn, this makes it possible to study natives' task adjustment across local labor markets, education groups, gender, and firm characteristics at a level of detail that is rarely available in existing work.

The rest of the paper proceeds as follows. Section 2 describe the data used in our analysis and present descriptive statistics. Section 3 presents the empirical model and identification strategy. Section 4 presents the empirical results. Finally Section 7 concludes.

2 Data

In this section, we describe the data used in our analysis and present descriptive statistics. We rely on several data sources at the worker, occupation, firm, and local labor market levels. Details on variable construction are reported in Appendix A.

2.1 Labor and migration data

INPS — Our main data source is the employer–employee database from the Italian Institute of Social Security (INPS). We use annual administrative data on the universe of employees in the private non-agricultural sector for the period 2013–2019. The database includes all employment spells recorded by firms with at least one employee. It contains information on employee demographics, contract type (e.g., temporary vs. permanent), work schedule (part-time vs. full-time), monthly salary, and workplace municipality. During data cleaning, we retain, for each worker–firm pair in a given year, the employment spell with the highest salary. As a result, a worker may appear multiple times within the same year if they change employers or have multiple employer. We restrict our sample to workers aged 15–64 and include only observations with positive reported salaries, excluding those above the 99th percentile for each year.[1] Throughout the paper, we define a contract as a worker–employer relationship. In addition, the INPS *workers' registry* provides an anonymous identification codes for all workers, along with information on birthplace, gender, and year of birth.

UNILAV — The *UNILAV* database records all mandatory employment notifications (i.e., *comunicazioni obbligatorie* - compulsory communications) from 2008 to 2019. This allows us to identify at least one compulsory communication for approximately 16.5 million workers over the period of analysis.[2] The database includes information on contract start dates and workers' educational qualifications. Most importantly, UNILAV provides data on workers' occupations based on the five-digit ISCO code from ISTAT's CP2011 classification, which includes 796 distinct job categories. The occupation code is recorded once whenever a contractual change occurs and a mandatory employment notification is submitted.

CERVED — Firm-level information on incorporated businesses is provided by the CERVED dataset. This database includes data on firms' balance sheets and income statements. We use information on revenues, capital, material costs, and employment to compute average capital intensity and average efficiency at the local labor market level, following De Loecker and Warzynski (2012) and Forlani et al. (2023). The sample is slightly unbalanced toward larger firms, with small firms somewhat underrepresented.

[1] This dataset does not include information on unemployment or self-employment.

[2] Mandatory notifications occur in four contractual cases: (i) when a contract begins, (ii) when a contract terminates, (iii) when a transformation occurs (e.g., a change of task or a shift from part-time to full-time), and (iv) when a contract is extended.

ISTAT — The *Italian National Statistical Office* (ISTAT) provides several datasets essential to our analysis. First, we obtain municipality-level data on the stock of migrants, which covers the period 2013–2019 and is used to construct our main explanatory variable. We also use data from 2003—the earliest available year—to build the instrumental variable. A migrant is an individual with a non-Italian citizenship. In addition, we incorporate residence permit data from 1991 to construct a second instrumental variable for robustness checks, following Barone et al. (2016). ISTAT also provides information on the territorial linkages between municipalities and local labor markets (*Sistemi Locali del Lavoro*) and changes administrative units.

Dataset construction — We now summarize the main steps in constructing the estimation sample, while details are provided in Appendix A.1. The key challenge in building the database lies in the different structures of the two main worker-level data sources: INPS and UNILAV. The INPS database includes all *active contracts* in a given year, whereas UNILAV only records *mandatory communications* in the year the notification occurs. Consequently, if a contract remains active in subsequent years, the worker does not reappear in UNILAV, and information on their occupation (ISCO code) and educational level is not updated (occupation is not recorded in the INPS employer-employee database). To address this, we reconstruct workers' employment histories by merging the two data sources.

Thus, the resulting sample includes individuals who experienced at least one contract change during 2008–2012 and were still employed during the estimation period (2013–2019), as well as those who had at least one mandatory communication between 2013 and 2019 and remained employed thereafter (including job changers). The sample excludes long-term workers—those who entered the labor market before 2008 and had no subsequent contract changes. For these workers, although we can observe an active contract, their ISCO code is missing. This is the reason why the average age of workers in the estimation sample is relatively low: 38 years. [3] Finally, the sample includes only active contracts, so that our analysis focuses on existing employment relationships rather than unemployment or transitions out of employment.

2.2 INAPP & Routine Intensity Index

We gather information on occupational characteristics from the *Indagine Campionaria sulle Professioni* (ICP), a survey conducted by the *Istituto Nazionale per l'Analisi delle Politiche Pubbliche* (INAPP) in 2007 and 2013. The ICP survey provides detailed data on skill requirements for all five-digit occupations (796 CPC 2011 codes) and is the only European survey that extensively replicates the American O*NET (Cirillo et al., 2021). Since ICP is specifically conducted on Italian workers, it offers a more accurate measure of the skill content of occupations within the Italian labor market, mitigating potential biases arising from structural differences with the U.S. labor market and production technologies. Furthermore, compared to previous research, we can rely on a substantially

[3] In a robustness analysis, we restrict the estimation sample to workers aged below 40. It is possible that most of the variation in the routinization index is driven by younger workers, who are more likely to change jobs and therefore more frequently appear in the mandatory communications data.

larger set of occupations (295 in Ottaviano et al. (2013) or 322 in Consoli et al. (2023)).

Thus, ICP survey is crucial for our analysis as it allows us to assess the skill content of Italian occupations, such as routine and manual task intensity, as well as work attitudes. This information enables us to quantify the intensity of routine, manual, and cognitive tasks for each occupation (Autor et al., 2003).

In particular, we make a clear distinction between tasks and skills: while a job may consist of a set of tasks, these tasks can be performed by workers with different skill level. Routine tasks are defined as those that require minimal autonomy and are characterized by high levels of repetition, typically performed on a fixed or regular basis. These types of tasks can also be performed by workers with low proficiency in the local language and limited qualifications, typically migrants in Italy. Conversely, non-routine tasks are not easily codified and demand abilities such as adaptability, intuition, and problem-solving. These tasks can involve both manual and abstract work, such as nursing or teaching.

Following Autor and Dorn (2013) and Cirillo et al. (2021), we measure the routine task intensity (RTI) of and occupation by combining information on task intensity from the ICP survey. For each occupation j, the routine task-intensity index is computed as follows

$$RTI_j = (\ln RC_{j,07} + \ln RM_{j,07}) - \ln NRM_{j,07} - (\ln NRCA_{j,07} + \ln NRCI_{j,07}), \tag{1}$$

where RC, RM, NRM, NRCA, and NRCI are, respectively, the routine cognitive, the routine manual, non-routine manual, Non-routine cognitive analytical, and Non-routine cognitive interpersonal input in each occupation j in 2007. [4] The measure is increasing in the importance of routine task (manual and cognitive) and decreasing the non-routine components. As an example, the most routinized jobs include switchboard operators, interviewers and professional surveyors, cashiers, and laundry machine operators. Jobs with a medium level of routinization include firefighters and food production technicians. Finally, less routinized jobs include museum technicians, party and association executives, political scientists, professional educators, and aerospace technicians. Even if some jobs are highly routinized, they still require cognitive ability or advanced language knowledge—for instance, interviewers and professional surveyors. For this reason, we extend our analysis by including different components of the RTI, such as NRCA and NRCI.

2.3 Descriptive Statistics

Before turning to the empirical model, we present an overview of the sample statistics. First, Table 1 reports summary statistics for the main variables used in the analysis. Panel A presents figures for all workers—both migrants and natives—registered in the INPS data. [5] Migrant workers display a higher average routinization index compared with Italians, indicating that migrants are

[4] The tasks are measured on a zero to ten scale. The RTI index is rescaled on a range from 0 to 1, where one is the maximum level of routinization. For more details, see Cirillo et al. (2021) and Appendix A.2 for the questionnaire.

[5] Statistics are computed on a sample with one observation per individual and year. For each individual we keep the best paid contract in a given year.

more concentrated in routine-intensive occupations. This gap becomes widens when accounting for differences in workers' skill levels: unskilled migrants are predominantly employed in highly routinized jobs. This pattern suggests that migrants may substitute native workers in routine occupations, pushing natives toward less routinized tasks. Finally, among the employed, the share of women is lower among the migrant compared to native workers (36 versus 45) and migrants receive lower average daily wages (€50.6 compared with €58.1).

Then, Panel B focuses on Italian workers by gender. Men exhibit higher routinization levels (RTI = 0.616) and are more frequently employed full-time (75 percent) but are less likely to be skilled compared with women. Women earn lower daily wages (€49.7 versus €66.0 for men) and are slightly younger on average. Overall, these descriptive patterns highlight both occupational and gender segmentation in the Italian labor market, as well as the more routine-intensive nature of migrant employment.

Table 1: Descriptive Statistics[a]

Panel A	All workers				
	RTI				
	All	Unsk	Skilled	Share of employed women	Daily wage
Migrant	0.663	0.668	0.482	0.361	50.62
Italian	0.597	0.614	0.439	0.448	58.13
All	0.609			0.432	57.62
Panel B	Italian				
	RTI	Age	Full-Time %	Skilled worker %	Daily wage
Men	0.616	38.580	0.746	0.087	66.010
Women	0.572	37.174	0.469	0.123	49.710
All	0.597	37.95	0.622	0.103	58.133

[a] Source:INPS. Upper panel show statistics for both native and migrant worker with a contract registred at INPS. Lower panel report statistics for Italian workers by gender.

We now turn our attention to the geographical distribution of jobs and migrants. Figure 1 displays the average RTI index by local labor market (LLM). The data suggest that employment in routinized jobs is more prevalent in the South of Italy. With the exception of a few large local labor markets, contracts in the Center-North of the country tend to be associated with less routinized occupations.

In addition, the geographical distribution of the data suggest a positive correlation between the average level of routinization required by occupations and the stock of migrants across LLM. Figure 2 shows that areas with larger share of migrants have on average more workers which are employed in less routinized jobs, while areas with less migrants. More precisely, Figure 1 indicates that about 19.5% of LLMs display a high RTI index and a low migration rate, whereas 21% have both a low RTI and a high migration rate. Only around 3% of LLMs in 2013 exhibit both high routinization and high migration levels.

The preliminary analysis shows a negative correlation between job routinization and the migrant labor supply at LLM. The descriptive evidence for Italy, together with findings from the existing literature, suggests that migrants may push native workers toward less routinized jobs, where natives hold a comparative advantage. In the next section, we present the empirical strategy used to identify

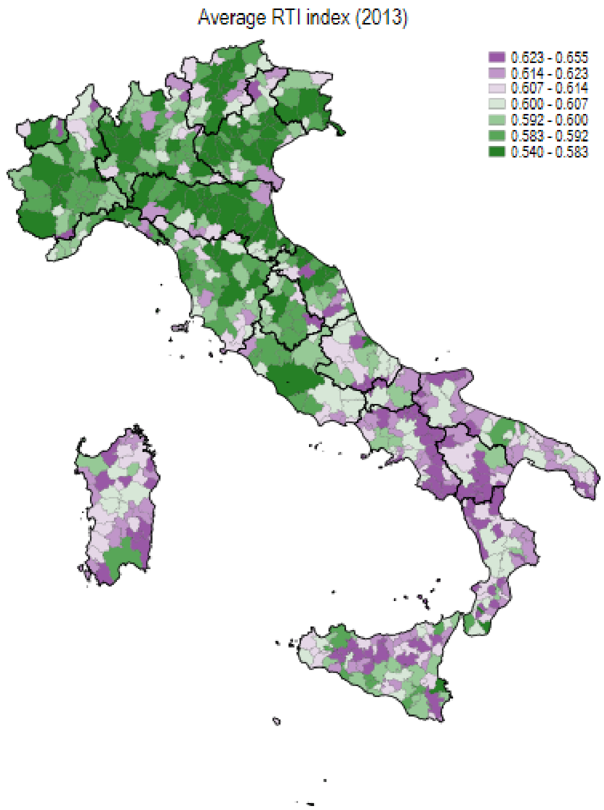

Figure 1

the causal effect of migrant-induced labor supply shocks on the routinization level of jobs held by Italian workers.

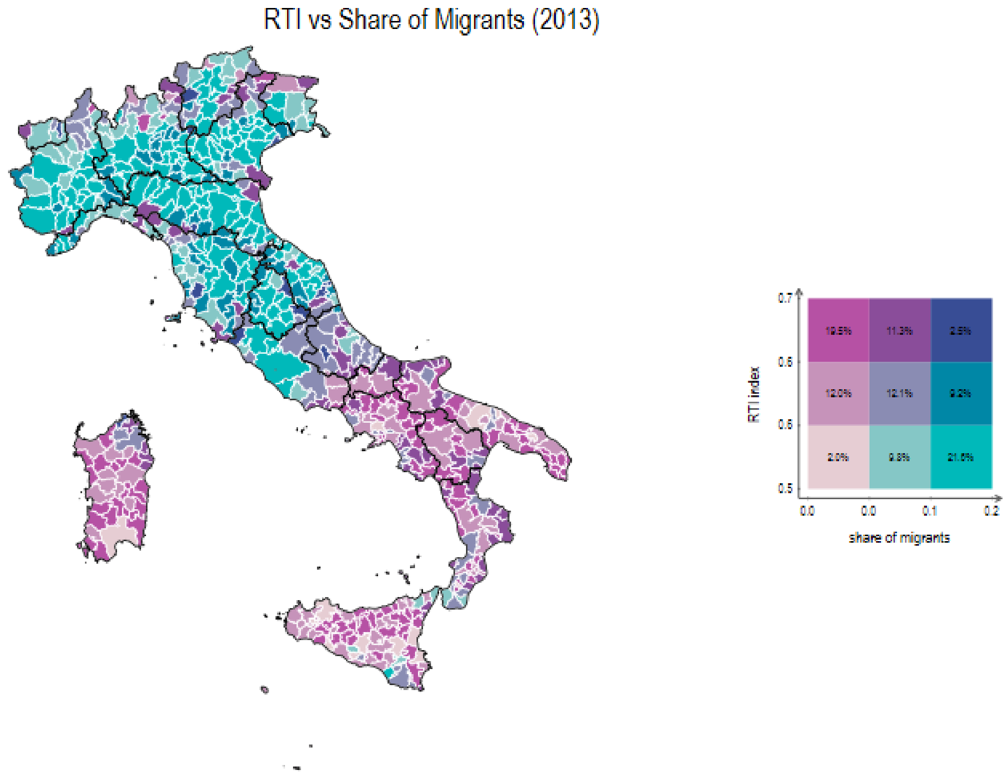

Figure 2

3 Empirical analysis and identification strategy

We aim at estimating the effect of migrants labour supply on the degree of job routinization, both at the individual and aggregated level, for Italian workers. At the individual level, in the spirit of Foged and Peri (2016), we identify the effect of migration shock at LLM on native workers by incorporating various sets of fixed effects that incorporate individual dimension. The estimated regression has the following structure

$$y(j)_{iflt} = \alpha_0 + \beta Mig.Share_{lt} + \boldsymbol{\gamma}\mathbf{x_{it}} + \delta_{rt} + \delta_{st} + \eta + u_{ijlt} \tag{2}$$

where $y(j)_{iflt}$ is the outcome variable for worker i employed by firm s, in occupation j, in LLM l at time t, and u_{ijlt} is the error term. Our primary outcome of interest is the degree of routinization in occupations held by Italian workers, as measured by Eq. 1 and its components (e.g., the intensity of Non-Routine Cognitive tasks). The empirical model includes different type of individual fixed effects η. These fixed effects allow us to estimate how a worker's task composition changes when the migrant share in the local labor market varies—while holding constant all time-invariant differences in individual characteristics.

More precisely, η represents worker-level fixed effects, which can be combined with additional units of observations, such as firm f or local labor market (LLM). We provide alternative estimates of

Eq.2 by incorporating or worker-firm, or worker-local labor market (LLM) fixed effects, or individual fixed effect only. In the first case, β captures changes in the degree of routinization within firms (i.e., changes in the occupation of workers within the same company). In the second case, we consider the effect of migration on native occupation across firms within the same local labor market, i.e., how migration affects natives' occupational tasks across firm within the same LLM. In the latter case, individual fixed effects, we assess the role of migration for individuals that moves across LLM, i.e., , allowing us to identify how routinization changes for workers who move across LLMs. [6]

Our estimation includes also a vector of time-varying individual characteristics such as age (log) and working experience (log) along with region-by-year (δ_{rt}) and industry-by-year (δ_{st}) fixed effects to control for asymmetric shocks across regions and industries. [7] Finally, to account for the correlation of errors within local labor markets across individuals-spell and year, we cluster standard error at LLM level.

We account for the possibility that the occupational complexity of workers with different characteristics responds differently to changes in the migrant labor supply within a LLM. To this end, we estimate Eq.2 by skill and by skill- gender level. First, we examine whether the effect of migrant labor supply varies in function of on workers' educational levels (with or without a college degree). As previously observed, skilled workers—both native and foreign—tend to experience lower levels of job routinization (see Table 1).

The main explanatory variable is $Mig.Share_{lt}$, which captures the relative supply of migrants at the local labor market (LLM) level. It is defined as:

$$Mig.Share_{lt} = \frac{Migrant_{lt}}{Pop_{lt}} \tag{3}$$

where $Migrant_{lt}$ denotes the total number of migrants residing in LLM l at time t, and Pop_{lt} is the total resident population.[8] The variable $Mig.Share_{lt}$ therefore approximates the local supply of migrant labor and allows us to test whether areas with a larger migrant presence exhibit lower levels of job routinization among native workers. The identification of the causal effect through $Mig.Share_{lt}$, however, raises several endogeneity concerns, which might bias the estimate of β in Eq. 2.

3.1 Identification Strategy

As the location in immigrant share across LLM over time is likely correlated with several omitted economic variables (i.e., not random), the Ordinary Least Square estimates of Eq.2 will not identify the causal effect of immigration on the occupation characteristic of Italian workers even including

[6]As a robustness check, we also estimate the model on the subsample of individuals who never change LLM of employment, in order to control for potential displacement effects associated with worker mobility

[7]In Italy there are 21 regions while industry are defined at one digit NACE rev2 classification (12 sections).

[8]Migration data are collected at the municipality level from ISTAT and then aggregated to the LLM level. Following Forlani et al. (2015), we proxy labor supply with the total migrant population, which allows us to account for migrants who may be employed in the informal or black market. A migrant is defined as any individual without Italian citizenship.

a batteries of fixed effects. The labor supply of migrants might be correlated with both current and past characteristics of LLM, which influence the economic outcomes of natives as well as the location decisions of migrants. For example, we might expect economically booming areas to attract more migrants while simultaneously offering fewer routine jobs to natives compared to stagnating regions. This positive correlation could result in an upward bias in the estimation of β in Eq.2. On the other hand, migrants may choose to settle in areas experiencing negative economic shocks to take advantage of lower prices, which could result in a downward bias.

We already observed that workers in the south of Italy tend to perform more routinized jobs compared to those in central and northern regions (Figure 1). Additionally, the data suggest a positive correlation between the average level of routinization required by occupations and the stock of migrants across LLM. Figure 2 shows that areas with larger share of migrants have on average more workers which are employed in less routinized jobs, while areas with less migrants. These two figures indicate a negative correlation between routinization and the migrant labor supply, and indicate that both phenomena may be influenced by economic shocks at the local labor market level. While the negative correlation aligns with existing literature, they also raise significant concerns regarding the causal identification for Eq.2.

Also including a rich battery of fixed effects (region X year and sector X year) would not eliminate the estimation bias arising from all potential omitted terms. The inclusion of individual X LLM fixed effects would partially capture the correlation between local economic condition and migrants' location choice. To address this issue, we rely on an Instrumental Variable (IV) shift-share approach pioneered by Card (2001). [9]

The shift-share approach redistributes the current stock of migrants (by origin) across LLMs, based on their past spatial distribution. Thus to instrument the migration, we employ the 2003 distribution of migrants by origin o across LLMs. We define the predicted number of migrants in LLM l and year t as:

$$\widehat{Migrant}_{lt} = \sum_{o} \frac{Migrant_{ol,2003}}{Migrant_{o,2003}} * Migrant_{o,t}^{-l} \tag{4}$$

where the first term is the share of migrant from origin o located in LLM l in 2003 (shift-share element. i.e., $\omega_{ol,2003}$). The exclusion restriction of Eq.4 relies on the assumption that the past share of migrants by origin (as of 2003) is uncorrelated with contemporaneous economic shocks. The identification of β stems from variations in the share $\omega_{ol,2003}$ across locations (Borusyak et al., 2025; Goldsmith-Pinkham et al., 2020). It is also important to underline that once we include in our estimation also LLM fixed effects (i.e., individual x LLM) these fixed effects will absorb any cross-LLM variation in immigrant origin shares. In this case the identifying variation comes from cross-time variation in the national stock of migrant by country of origin (Borusyak et al., 2021).

To further isolate the migration component ($Migrant_{o,t}^{-l}$) that could be correlated with local labor market economic shocks, we propose a slightly modified version of the shift-share instrument.

[9] This strategy might be subject to criticism (Jaeger et al., 2018). In our robustness analysis (Section 6), we perform a set of checks to our IV approach as proposed by Goldsmith-Pinkham et al. (2020).

[10] This adjustment involves redistributing the stock of migrants from origin o at time t between LLM l, excluding the portion attributable to local labor market l. The goal is to maintain consistency with the assumption that migrant stocks are, in effect, randomly assigned to countries of origin and not in function of economic shocks in l. Conversely, if the majority of migrants from o are determined by the economic conditions of a specific area, the instrument may still correlate with unobserved factors. [11]

Finally, we compute the imputed share of immigrants in each in LLM (Eq. 3) as follows,

$$\widehat{Mig.Share}_{lt} = \frac{\widehat{Migrant}_{lt}}{Pop._{l,2003}}, \tag{5}$$

by normalizing the predicted number of migrants in local labor market l at time t by the population level in 2003.

4 Estimation Results

Table 3 reports the estimation results for the baseline model. We estimate Eq. Eq.2 for both low and high skilled native workers and we shows only the coefficient of interest β from the baseline model. More precisely, β quantifies the impact of a 1 percentage point increase in the migrant population on the routine tasks performed by native workers.

Each column represent a different regression accounting for varying combination of fixed effects, skill levels, and estimation methods. From (1) to (4), we control for individual-firm fixed effects, (5) to (9) for individual-LLM, and (10) to (13) for individual fixed effects alone.

The results reported in Table 3 are interesting and consistent with the idea of complementary between natives and migrants in job task. We find a statistically significant effect of migration on routine task intensity by native workers only for the unskilled ones. In other terms, unskilled native workers tend to perform fewer routine tasks in their jobs when they work in areas with a higher concentration of migrants. The same effect is not detected for skilled workers that seem not affected by migrants' labor supply. This in consistent with the idea that migrants in Italy performs more routinized task in their jobs (see Tab 1).

We can refine our analysis by examining the effect of migration for units of variation. Col. 2 presents the impact of migration on unskilled workers within companies (i.e., workers that do not change employer). Specifically, a 1 percentage point increase in the migrant labor supply results in a 0.16 p.p. reduction in the RTI index. Compared to the average RTI value of 0.61 for unskilled, this corresponds to a 0.26% decrease in the RTI index.

The marginal effect appears relatively small, which could be due on the fact the exploiting the variation of migration for those native workers who remain within the same firm. In other words, it is we capture the effect of migration on workers who retain the same contract within a ISCO

[10] Similar adjustments have been implemented by Barone et al. (2016); Orrenius and Zavodny (2015).

[11] More precisely, we minimize concerns about the possibility that a particular nationality is drawn to an economic shock in LLM l.

Table 2: Baseline Estimates: RTI Index

OLS Model	(1)	(2) Unskilled	(3)	(4)	(5) Skilled	(6)
	F × W	LLM × W	W	F × W	LLM × W	W
Mig. Share	-.0991***	-.0976***	-.0731***	-.0627***	-.0515	-.1867***
	(.01)	(.0195)	(.0151)	(.0149)	(.0391)	(.0335)
Log(Age)	-.101***	-.0699***	-.0449***	-.082***	-.3241***	-.5091***
	(.0035)	(.0035)	(.0033)	(.0131)	(.0229)	(.0337)
Log(Exper.)	.009***	8.7e-04***	-.0037***	.0043***	.0031***	.0046***
	(3.6e-04)	(2.4e-04)	(2.5e-04)	(3.3e-04)	(6.1e-04)	(5.5e-04)
Observations	41,117,238	43,922,271	46,404,880	5,478,574	5,876,307	6,278,742
R^2	.9063	.8558	.8166	.9180	.8306	.7523
IV Model	(1)	(2) Unskilled	(3)	(4)	(5) Skilled	(6)
	F × W	LLM × W	W	F × W	LLM × W	W
Mig. Share	-.1135***	-.1967***	-.0603**	-.0561*	-.2667	-.1781***
	(.0133)	(.0278)	(.0191)	(.0230)	(.1699)	(.0420)
Log(Age)	-.101***	-.0703***	-.0448***	-.0819***	-.3260***	-.5091***
	(.0035)	(.0035)	(.0033)	(.0131)	(.0229)	(.0337)
Log(Exper.)	.009***	8.8e-04***	-.0037***	.0043***	.0032***	.0046***
	(3.6e-04)	(2.4e-04)	(2.5e-04)	(3.3e-04)	(6.0e-04)	(5.4e-04)
Obs.	41,117,238	43,922,271	46,404,880	5,478,574	5,876,307	6,278,742
R^2	8.5e-04	2.0e-04	3.8e-04	2.1e-04	.0016	.0038
F-test (KP rk Wald)	323.6	101.1	288.3	211.4	13.04	257.0

Dependent variable is the RTI index (Eq. 1). All specifications include industry-by-year and region-by-year fixed effects. Constant included. Standard errors in parentheses, clustered at the LLM level. F × W: firm by worker fixed effects. LLM × W: Local Labor Market by worker fixed effects. W: worker fixed effects. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

code. [12] Even if a worker's tasks change, the ISCO code does not vary, resulting in no measurable variation in job routinization. So the effect is captured only for those workers who change contract (and ISCO) within the same company.

Instead, if we consider the effect of migration among those who change companies within the same LLM (Col.5 -8), we observe a greater contribution of migration to the variation in the RTI index. Specifically, a 1 percentage point increase in the migrant labor supply results in a 0.24 p.p reduction in the RTI index. Compared to the average RTI value of 0.61 for unskilled in the sample, this corresponds to a 0.4% decrease in the RTI index. [13] We estimate the effect foir workers who change establishment within the same LLM: in this case it is more likely that change in the employer is associated with a change in the occupation and consequently a measured variation in the RTI index.

[12]Fixed effects vary at contract-individual level. A worker might renew the contract but not change the job (i.e., the ISCO) within the same company.

[13]A similar difference in the magnitude of coefficients across models and in sign of the omitted variable bias is observed by Foged and Peri (2016).

Table 3: Fixed Effect Regression - Routine Task Index by skill level[a]

	Worker Firm				Worker LLM				Worker			
	Unskilled		Skilled		Unskilled		Skilled		Unskilled		Skilled	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Mig.Share	-.1674***	-.1655***	-.0149	.0212	-.1875***	-.2456***	-.0061	-.055	.0021	.0027	-.0037	-.0024
	(.0158)	(.0251)	(.0125)	(.0211)	(.0207)	(.0292)	(.0181)	(.0484)	(.0015)	(.0024)	(.0045)	(.0073)
Obs.	51467833	51467833	6226386	6226386	54537114	54537114	6529471	6529471	57246561	57246561	6912886	6912886
R2	.7468	.0023	.845	1.5e-04	.7768	7.7e-04	.8468	3.3e-05	.7919	2.4e-06	.8427	9.0e-07
F-Test		345.6		212.4		234.1		83.56		284.6		243.4
	Fixed Effects											
Region x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Ind.	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
LLM x Ind	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Ind	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

[a] Dependent Variable: RTI index (Eq.1). The sample include firm-indivual relation in the period 2013-2019. Control variables: age and expertise of worker. Constant included in the model. F-Test: Kleibergen-Paap rk Wald F statistic. Stadard errors in parenthesis are clustered at LLM level. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

In both cases, the variation is relatively small. To give a practical example from Column 6, a worker performing the median job in terms of routinization (e.g., firefighters or food production technicians) would switch to a relatively similar job(e.g., electronics technicians). Thus, the results suggest that migration induces native workers to shift toward less routinized jobs within their feasible set of occupations for their background and education.

Finally, we do not detect any statistically significant effect while we consider the effect of migration within the whole work history of natives.

In all the cases, instrument seem to have a good predictive power with and F-test value above 100.

4.1 Female vs Male outcomes

Now, we try to analyze the effect of migration between workers gender. In Table 4, we just report the IV analysis results for man and women separately. [14] As in the previous case, workers in areas with a large fraction of migrants are less likely to perform routinized tasks in their jobs; in particular the effect is slightly larger once we consider variations in the occupations for workers within the same LLM but across firms (Col.3-4). In particular, a 1 percentage point increase in the migrant labor supply results in a 0.26% reduction in the RTI index for women and reduction of 0.2% for men. Compared to the average RTI value, this corresponds to a 0.44% decrease in the RTI index for women and a 0.32% for men.

In all the cases, instrument seem to have a good predictive power with and F-test value above 100.

4.2 Open the box

Now we can consider how different components of the RTI index respond to changes in the migrants' labor supply. In particular, we analyze the impact of migration on routine and non-routine tasks,

[14] We do not find any statistically significant effect for skilled workers for both male and females.

Table 4: Fixed Effect Regression for unskilled - Routine Task Index by gender level[a]

	Worker Firms		Worker LLM		Work er	
	Man	Female	Man	Female	Man	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Mig.Share	-.1365***	-.1307***	-.1963***	-.2585***	.0027	.0028
	(.0206)	(.0234)	(.0292)	(.0306)	(.0028)	(.004)
Obs.	28826304	22233005	30680888	23769922	32481951	24764610
R2	.0014	7.6e-04	3.4e-04	1.8e-04	2.0e-06	3.3e-06
F-Test	335.3	332.6	199.3	170	284.1	278.2
			Fixed Effects			
Region x Year	Yes	Yes	Yes	Yes	Yes	Yes
Sector x Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Ind.	Yes	Yes	No	No	No	No
LLM x Ind	No	No	Yes	Yes	No	No
Ind	No	No	No	No	Yes	Yes

[a] Dependent Variable: RTI index (Eq.1). The sample include firm-indivual relation in the period 2013-2019. Control variables: age and expertise of worker. Constant included in the model. F-Test: Kleibergen-Paap rk Wald F statistic. Stadard errors in parenthesis are clustered at LLM level. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

both manual and cognitive (see elements Eq.1). Table 5 reports the estimation results for both unskilled (Panel A) and skilled (Panel B) native workers. For unskilled workers, a increase in migrants' labor supply is associated with a decrease in both routine and non-routine manual tasks (RM and NRM, respectively) and an increase in non-routine cognitive tasks (NRC), but we do not detect any effect on routine cognitive tasks (RC).

Consistent with prior findings, effects are stronger for those who switch companies within the same local labor market (Col.5-8) compared to those who stay within the same company (Col.1-4), and there is no effect once we consider the effect of migration within the work history of the natives (Col. 9-12).

For skilled workers (*Panel B*), we find weaker effects which are similar to those for unskilled workers. In particular, for non-routine manual (NRM) and cognitive (NRC) tasks when using worker-LLM fixed effects.

In all the cases, instrument seem to have a good predictive power with and F-test value above 100.

5 Robustness check

5.1 Sector and local development level

In this robustness check, we leverage economic disparities in technological advancement across firms and local labor markets. The underlying idea is that migration drives shifts in occupational types among native workers in regions and firms that are more dynamic and efficient, i.e., in areas where it is more likely a movement across occupations or in companies which are able to exploit changes in the labour supply. Conversely, we do not expect substantial changes in the occupations or tasks performed by workers in economically stagnant regions or less efficient firms.

In this particular exercise, we exploit the firm level information reported in the *CERVED*

Table 5: Fixed Effect Regression - Routine Task Index by skill level and components [a]

Panel A	Unskilled Worker											
	Worker Firm				Worker LLM				Worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	RC	RM	NRC	NRM	RC	RM	NRC	NRM	RC	RM	NRC	NRM
Mig.Share	.0389	-.2079***	.7873***	-.3234***	.0542	-.3036***	1.186***	-.2456***	-.0045	9.4e-04	-.0177	.0038
	(.0222)	(.0423)	(.1062)	(.0507)	(.0412)	(.0605)	(.123)	(.0292)	(.0054)	(.0029)	(.0109)	(.0028)
Obs.	51467833	51467833	51467833	51467833	54537114	54537114	54537114	54537114	57246561	57246561	57246561	57246561
R2	3.2e-04	.0045	.0015	.0047	1.1e-04	.0017	4.5e-04	7.7e-04	2.5e-08	2.2e-06	1.9e-06	1.7e-06
F-Test	345.6	345.6	345.6	345.6	234.1	234.1	234.1	234.1	284.6	284.6	284.6	284.6
Panel B	Skilled Worker											
	Worker Firm				Worker LLM				Worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	RC	RM	NRC	NRM	RC	RM	NRC	NRM	RC	RM	NRC	NRM
Mig.Share	.0596	-.0387	.0582	-.1183***	.1119	-.1475*	.5275***	-.3527***	-.0014	-.0053	.0039	-.0024
	(.0372)	(.0364)	(.0702)	(.0343)	(.0963)	(.0734)	(.1462)	(.0792)	(.0139)	(.0127)	(.0228)	(.0073)
Obs.	6226386	6226386	6226386	6226386	6529471	6529471	6529471	6529471	6912886	6912886	6912886	6912886
R2	4.1e-07	8.8e-05	3.8e-04	2.4e-04	-3.7e-06	2.3e-05	5.0e-05	5.1e-05	2.7e-07	8.3e-07	5.0e-08	9.0e-07
F-Test	212.4	212.4	212.4	212.4	83.56	83.56	83.56	83.56	243.4	243.4	243.4	243.4
	Fixed Effects											
Region x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Ind.	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
LLM x Ind	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Ind	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

[a] Dependent Variables. RC: routine cognitive. RM: routine manual. NRC: non-routine cognitive. NRM: non-routine manual. Control variables: age and expertise of worker. Constant included in the model. F-Test: Kleibergen-Paap rk Wald F statistic. Standard errors in parenthesis are clustered at LLM level. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

database. For this purpose, we measure for each firm the amount of fixed assets and the firms' productivity (as a residual of a Cobb Douglas production function defined at sector level De Loecker and Warzynski (2012)). Using as a reference year the 2010, (first year of observation for CERVED data), we divide firms in two groups using three different criteria.

1. For each 2-digit ATECO 2007, we calculate the median productivity value in 2010 ($TFP^{p50}_{s,10}$). We then categorize firms into two groups based on whether their productivity is above or below this sectoral threshold, and estimate Eq.2 separately for each group.

2. For each 2-digit ATECO 2007 and year, we compute the mean productivity value ($\overline{TFP}_s$) and we use it to normalize the productivity of firm x in sector s, i.e., $\widetilde{TFP}_x = TFP_{xs}/\overline{TFP}_s$. Then for each LLM, we calculate the median of the normalized productivity for year 2010 ($TFP^{p50}_{sl,10}$). Finally, we identify if a firm is above or below the median value of normalized productivity within a LLM.

3. Finally, for each 2-digit ATECO 2007, we calculate the median value of fixed assets in 2010 ($K^{p50}_{sl,10}$). We then categorize firms into two groups based on whether their level of fixed assets is above or below this sectoral threshold, and estimate Eq.2 separately for each group.

Table 6 reports the estimation results for unskilled workers. As before, the effect of migration is substantial when incorporating firm-worker and local labor market (LLM) fixed effects (Panels A and B, respectively). Specifically, task shifts among Italian workers appear to occur primarily among those who remain with, or are employed by, the most efficient firms—measured relative to sector-level productivity (criterion 1) and LLM median productivity (criterion 2). No such differences emerge when workers are grouped by firm size, as measured by capital value (criterion 3). In all the cases, instrument seem to have a good predictive power with and F-test value above 100.

Table 6: Fixed Effect Regression - Routine Task Index by firm size[a]

Panel A	Worker - Firm FE					
	Sector		LLM		Sector	
	TFP$< TFP^{p50}_{s,10}$	TFP$> TFP^{p50}_{s,10}$	$\widetilde{TFP}_x < TFP^{p50}_{sl,10}$	$\widetilde{TFP}_x > TFP^{p50}_{sl,10}$	K$< K^{p50}_{s,10}$	K$> K^{p50}_{s,10}$
Mig.Share	-.0525	-.1074**	-.0536	-.1186***	-.1152**	-.1018**
	(.0479)	(.034)	(.0447)	(.0338)	(.0381)	(.0308)
Obs.	2642108	12536229	2677044	12506955	2802513	12372350
R2	.8506	.8276	.8516	.8272	.8446	.829
F-Test	200.3	298.3	168.9	307.9	181.5	311.1
Panel B	Worker - LLM FE					
	Sector		LLM		Sector	
	TFP$< TFP^{p50}_{s,10}$	TFP$> TFP^{p50}_{s,10}$	$\widetilde{TFP}_x < TFP^{p50}_{sl,10}$	$\widetilde{TFP}_x > TFP^{p50}_{sl,10}$	K$< K^{p50}_{s,10}$	K$> K^{p50}_{s,10}$
Mig.Share	-.0986	-.204***	-.1484	-.2089***	-.2423*	-.2094***
	(.1042)	(.0434)	(.1064)	(.0425)	(.0011)	(7.9e-04)
Obs.	2647963	12899541	2684652	12860763	2810914	12720024
R2	8.3e-06	4.4e-04	1.0e-05	4.4e-04	3.8e-05	4.0e-04
F-Test	48	154.9	40.19	160.3	45.22	160.9
Panel C	Worker FE					
	Sector		LLM		Sector	
	TFP$< TFP^{p50}_{s,10}$	TFP$> TFP^{p50}_{s,10}$	$\widetilde{TFP}_x < TFP^{p50}_{sl,10}$	$\widetilde{TFP}_x > TFP^{p50}_{sl,10}$	K$< K^{p50}_{s,10}$	K$> K^{p50}_{s,10}$
Mig.Share	.002	-.0057	-.007	-.0027	-.0322	-.004
	(.0189)	(.0067)	(.0209)	(.0063)	(.0198)	(.0063)
Obs.	2713251	13546913	2743601	13515177	2879751	13362097
R2	1.1e-05	1.9e-06	8.7e-06	2.3e-06	2.2e-06	3.1e-06
F-Test	201.7	224.7	179.9	233.7	181.9	238.2

[a] Dependent Variable: RTI index (Eq.1). The sample include firm-indivual relation in the period 2013-2019. Control variables: age and expertise of worker. Constant included in the model. F-Test: Kleibergen-Paap rk Wald F statistic. Stadard errors in parenthesis are clustered at LLM level. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

5.2 Aggregated Data

In this section, we estimate Eq.2 by aggregating data. Specifically, we define the average value of RTI index (Eq.1) and its components by skill, LLM, and year level. The estimation results for aggregated data align with the corresponding micro-level findings. Specifically, the data suggest that jobs held by unskilled workers in local labor markets with a high share of migrants are less routinized (Panel A) and involve fewer manual tasks for both skilled and unskilled workers (Panels A and B). In all the cases, instrument seem to have a good predictive power with and F-test value above 100.

Table 7: LLM aggregates - Skill Level Anlysis[a]

Panel A			Unskilled worker average task		
	RTI	RC	RM	NRC	NRM
Mig.Share	-.115**	-.0632	-.1518***	.4326***	-.2077***
	(.0432)	(.0501)	(.0517)	(.1387)	(.0472)
Obs.	4270	4270	4270	4270	4270
R2	.4039	.1434	.3395	.4743	.5583
F-Test	133	133	133	133	133
Panel B			Skille worker average task		
	RTI	RC	RM	NRC	NRM
Mig.Share	.005	.0744	-.2959***	.0657	-.3061***
	(.0412)	(.0806)	(.08)	(.1393)	(.0979)
Obs.	4270	4270	4270	4270	4270
R2	.1261	.0161	.0608	.2169	.0871
F-Test	133	133	133	133	133

[a] Dependent Variables is the average value of the follwiign variable by skill, LLM and year. RTI index (Eq.1). RC: routine cognitive. RM: routine manual. NRC: non-routine cognitive. NRM: non-routine manual. Each observetaion is defined at LLM and year level. Control variables are the avereage value at LLM-year level of the following variables: age, expertise of worker, share of female, share of skilled worker, daily wage. Constant and region by year fixed effects included in the model. F-Test: Kleibergen-Paap rk Wald F statistic. Stadard errors in parenthesis are clustered at LLM level. Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

6 IV validity

In this section, we test the validity of our results by considering different shares in the instrumental variable (Eq. 4) and by testing the exogeneity of the shift-share instrument.

Instrument from 1991 — First, we estimate the baseline model using a different definition of the share. More precisely, we use residence permits in 1991 for extra-EU citizens to construct the share of the instrumental variable, rather than using the distribution of migrants by origin and LLM in 2003. In this case, the weight does not include EU citizens in 1991; differently from Eq. 4, we only redistribute the migration shift from extra-EU countries as in 1991. This excludes nationalities such as German and French, but still includes all countries from Eastern Europe and South America.

Table 8: Unskilled workers - 1991 instrument

			Worker Firm					Worker LLM					Worker		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	RTIz	RCz	RMz	NRCz	NRMz	RTIz	RCz	RMz	NRCz	NRMz	RTIz	RCz	RMz	NRCz	NRMz
share_SLL1	-.688***	-.0909	-1.082***	2.815***	-1.357***	-.9349***	-.1563*	-1.679***	3.856***	-2.117***	-.0022	2.7e-04	-.0037	.0129	-.0078
	(.0851)	(.0541)	(.1299)	(.3939)	(.1816)	(.0927)	(.0674)	(.1555)	(.411)	(.2055)	(.0041)	(.0118)	(.0066)	(.0234)	(.0059)
lnage	-.2001***	-.1433***	-.3641***	.6693***	-.4115***	-.1369***	-.1181***	-.2527***	.4333***	-.2807***	9.7e-04	5.5e-05	3.8e-04	-.0043	.001
	(.0108)	(.0084)	(.017)	(.0408)	(.0184)	(.0066)	(.0064)	(.0107)	(.0252)	(.0119)	(.0013)	(.0032)	(.0017)	(.0052)	(.0017)
lnexper	.0215***	.0183***	.0402***	-.0694***	.0458***	.0144***	.0134***	.0271***	-.0454***	.0309***	-7.5e-04***	-8.4e-05	-8.3e-04***	.0028***	-8.2e-04***
	(.0013)	(8.0e-04)	(.0019)	(.005)	(.0022)	(7.4e-04)	(7.3e-04)	(.0011)	(.0029)	(.0013)	(1.5e-04)	(3.2e-04)	(1.9e-04)	(5.1e-04)	(1.8e-04)
N	51200300	51200300	51200300	51200300	51200300	54256159	54256159	54256159	54256159	54256159	56933889	56933889	56933889	56933889	56933889
r2	-3.8e-04	3.3e-04	5.1e-04	-.0012	-2.3e-04	-.0017	1.1e-04	-.0036	-.002	-.0048	2.2e-06	2.1e-09	2.0e-06	1.5e-06	8.8e-07
widstat	116.6	116.6	116.6	116.6	116.6	115.1	115.1	115.1	115.1	115.1	112.7	112.7	112.7	112.7	112.7

[a] Dependent variable: Routine Task Index (Eq. 1). The sample includes firm–individual relations from 2013–2019. Control variables: age and experience of the worker. Constant included in the model. F-Test: Kleibergen–Paap rk Wald F statistic. Standard errors in parentheses are clustered at the LLM level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 reports the estimation results for unskilled workers only. We observe that the sign of the coefficients does not change compared to Table 3 and Table 5. However, the magnitude of the significant coefficients is larger. This may suggest that the effect of changes in job routinization by native unskilled workers is mostly driven by extra-EU workers who substitute natives in routine jobs.

Exclusion restriction validity — Following Orefice and Peri (2024), we conduct a series of robustness checks to assess the validity and reliability of our identification strategy. First, we test whether past economic shocks, such as changes in wages (between 2010–2012 and 2002–2012), are correlated with the instrumental variable, and in particular, with changes in the instrument at the local labor market level during the estimation period (2013–2019). The aim is to verify whether past economic shocks are correlated with the instrument. Since economic shocks can be persistent over time, we want to ensure that current economic shocks are not correlated with the instrument, which would violate the exclusion restriction.

Table 9 shows that long-term changes in the instrumental variable are not correlated with long- or short-term past economic shocks, measured by changes in the average weekly wage and the share of full-time contracts by LLM from 2010 to 2012 or from 2002 to 2012. These results reassure us about the validity of the exclusion restriction.

Table 9: Test for IV validity - Exogeneity of instruments to economic shocks

	(1) $\Delta W_{2012,2002}$	(2) $\Delta FT_{2012,2002}$
$\Delta Z_{2019,2013}$	.3959	-1.103
	(.6331)	(.7854)
Cons.	-.0354***	-.2094***
	(.0032)	(.0025)
Obs	610	610
R2	.3781	.6382
	(1) $\Delta W_{2012,2010}$	(2) $\Delta FT_{2012,2010}$
$\Delta Z_{2019,2013}$	-158.9	-.2306
	(103.6)	(.2003)
Cons.	-12.32***	-.036***
	(.5936)	(.0013)
Obs	610	610
R2	.2085	.3642

[a] Dependent variable. Variation in % of wages (W) and share of full time contract (FT) at LLM. $\Delta Z_{2019,2013}$ is the difference in the instrumental variable between 2013 to 2019. Standard errors in parentheses are clustered at the LLM level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

However, we can go further. As underlined by Borusyak et al. (2025), in this context identification relies on the exogeneity of the shares. Therefore, we test whether the shares from some particular ethnic groups are exogenous to local economic conditions in 2003. Following Goldsmith-Pinkham et al. (2020), we compute the Rotemberg weights to identify the most relevant origins for the instrument. As reported in Table 10, the most important origins, in order of importance, are Romania, Albania, China, Morocco, and the Philippines. These countries account for 50% of the total Rotemberg weights.[15]

Next, we test whether the shares of the top five origin countries (in 2003) are related to economic conditions in 2003. Table 11 shows that the shares of the most important origins according to the Rotemberg weight calculation are not correlated with wages in 2003. In other words, the past distribution of migrants in 2003 is not related to the level of wages in 2003. These statistics suggest that our identification strategy is robust and satisfies the exclusion restriction.

Table 10: Test for IV validity - Rotemberg weight stats

	$\hat{a}_k$	g_k	$\hat{\beta}_k$	95% CI
Filippine	0.0507	1.63e+05	-1.7220	(-1.9727, -1.4714)
Marocco	0.0662	4.55e+05	-1.3328	(-1.5028, -1.1627)
Albania	0.0704	4.96e+05	-1.3630	(-1.5251, -1.2010)
Cina	0.0705	2.57e+05	-1.8154	(-1.4270, -1.0162)
Romania	0.2450	1.08e+06	-1.3548	(-1.5171, -1.1924)

[a] Rotemberg weight statistics. $\hat{a}_k$ is the Rotemberg weight. g_k is the estimated migration. $\hat{\beta}_k$. $\hat{\beta}_k$ is the first stage statistics from regressing the endoguenus variable (Eq. 4,) in LLM on share k in LLM l.

Table 11: Test for IV validity - Rotember share exogeneity

	(1) $\omega_{l,2003}$Albania	(2) $\omega_{l,2003}$Romania	(3) $\omega_{l,2003}$China	(4) $\omega_{l,2003}$Philippines	(5) $\omega_{l,2003}$Morocco
$Log(wage)_{l,2003}$	3.751	-.689	.5666	-.2347	3.981
	(2.464)	(.6039)	(.7219)	(.2935)	(2.439)
Cons.	6.155***	6.162***	6.16***	6.161***	6.155***
	(.0075)	(.0064)	(.0064)	(.0063)	(.0074)
Obs.	610	610	610	610	610
R2	.5561	.5541	.5539	.5538	.5575

[a] Dependent variable $\omega_{l,2003}$ is the share of migrant by top origins in 2003 in LLM l. Robust standard errors are in parenthesis Significance level: * 0.10> value ** 0.05> value *** 0.01> value.

7 Conclusion

This paper studies how immigration affects the task content of native employment in Italy. Combining Italian administrative employer–employee records with occupation-level task measures from the INAPP–ISTAT Survey on Italian Occupations, we show that greater migrant exposure in local labor markets pushes native workers toward less routine jobs. This effect is strongest for less educated natives, while for more educated workers it is weaker. The adjustment is driven mainly by a decline in manual tasks and, among the low skilled, by an increase in non-routine cognitive tasks. These patterns hold for both men and women. Our findings support a task-based view of labor

[15] Rotemberg weights and shifts g_k are correlated at 97%.

market adjustment to immigration. Rather than affecting natives only through wages or employment, immigration also changes what natives do on the job. In the Italian context, where migrants are concentrated in routine-intensive occupations, native workers appear to reallocate toward tasks in which they have a comparative advantage. This mechanism is consistent with imperfect substitutability between natives and migrants and helps explain why immigration need not result in simple displacement effects. The paper also shows that this adjustment is stronger when natives move across firms within the same local labor market and in more productive firms, suggesting that firm heterogeneity plays an important role in shaping responses to immigration. More broadly, the paper contributes by providing evidence for Italy, by measuring task content with the ICP rather than O*NET-based proxies, and by combining this classification with administrative data that allow a precise analysis of workers' employment trajectories. Overall, the evidence suggests that immigration reshapes native employment through task reallocation. Understanding immigration therefore requires a task-based perspective, particularly in labor markets where workers and firms differ substantially in their capacity to adapt.

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A Data Description

A.1 Database construction - Steps

In this section, we describe in detail how the estimation sample and the subsample used in the robustness analysis are defined. In particular, we outline the strategy adopted to merge information from the *worker registry*, the INPS database, and the *UNILAV* system of mandatory employment notifications.

1. We merge the *worker registry* with *UNILAV* and retain individuals for whom information on gender, year of birth, and citizenship is available. Moreover, for each mandatory communication associated with a contract, we keep those records that include information on educational attainment.

2. We retain mandatory communications from 2008 to 2012 (prior to the estimation sample). For each worker–firm relationship, we keep the most recent mandatory communication with a valid ISCO code. This resulting *list of workers* allows us to define the type of jobs held by workers as of 2013 (the beginning of the estimation period). Thus, the observations in the estimation sample for 2013 include workers who experienced a contract change during 2008–2012 (or in 2013).

3. We merge annual INPS data on contracts in the private, non-agricultural sector with the *Anagrafica delle imprese* (firm registry) to retrieve information on the ATECO 2007 sector of the employing company. We then merge these data with the list of workers from step 2. We drop workers for whom the workplace municipality is missing.

4. In the fourth step, we merge the worker–firm observations with the *UNILAV* database for 2013–2019. This step reconstructs workers' occupation codes (ISCO) and educational levels both backward and forward in time. We distinguish two cases:

   - For workers with at least one mandatory communication in 2008–2012, we assign the corresponding ISCO code to the same worker–firm relationship if it still exists in the estimation period. The worker retains that ISCO code until a new communication is observed. If additional communications occur between 2013 and 2019, the ISCO code is updated accordingly and remains valid until the next communication.
   - For workers whose first mandatory communication occurs in 2013–2019, the individual enters the estimation sample at that point and retains the ISCO code until a new communication is registered.

5. Finally, we link the worker–firm-level data with local labor market information by associating each municipality with its corresponding local labor market, according to the 2011 definition by ISTAT.

6. We trim the data as follows: (i) we retain only workers employed in ATECO 2007 industries; (ii) we drop observations with missing wage data or with wages above the 99th percentile of the distribution; and (iii) we remove multiple contracts held by the same worker with the same firm in a given year, keeping only the most relevant contract (the one with the highest salary).

A.2 RTI index

Here, we report the questions in INAPP-ISTAT Indagine Campionaria sulle Professioni (ICP) which are used to compute the RTI index Eq.1 (Cirillo et al., 2021).

- *Routine Cognitive (RC)*: Importance of repeating the same tasks. Importance of being precise and accurate. (Inverse of) Freedom to define tasks, priorities, and objectives.
- *Routine Manual (RM)*: Importance of controlling sequences of machinery or equipment. Importance of operating machinery and processes. Importance of performing repetitive movements.
- *Non-Routine Cognitive: Analytical (NRCA)*: Importance of analyzing data or information. Importance of thinking creatively. Importance of interpreting the meaning of tasks.
- *Non-Routine Cognitive: Interpersonal (NRCI)*: Importance of establishing and maintaining interpersonal relationships. Importance of guiding, directing, and motivating subordinates. Importance of training and developing other people.
- *Non-Routine Manual (NRM)*: Importance of operating vehicles, mechanical means, or equipment. Time spent using hands to handle, control, or feel objects, tools, or control systems. Importance of manual skills. Importance of spatial orientation.

The RTI index is fully consistent with the index used by Autor and Dorn (2013) and it is constructed for each of the j occupations as follows:

$$RTI_j = RC_j + RM_j - \left[\underbrace{NRCA_j + NRCI_j}_{NRC_j} + NRM_j \right]$$