

Do immigrants shield the locals? Exposure to COVID-related risks in the European Union

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Abstract

This article investigates the relationship between immigration and the exposure of native workers to health and labor-market risks arising from the COVID-19 pandemic in Europe. Using various measures of occupational risks based on European Union labor force survey data, we find that immigrant workers, especially those from lower-income member countries in Eastern Europe or from outside the EU, face greater exposure than their native-born peers to both income and health-shocks related to COVID-19. We also show that native workers living in regions with a higher concentration of immigrants are less exposed to some of the income and health risks associated with the pandemic. To assess whether this relationship is causal, we use a Bartik-type shift-share instrument to control for potential bias and unobservable factors that would lead migrants to self-select into more vulnerable occupations across regions. The results show that the presence of immigrant workers has a causal effect in reducing the exposure of native workers to various risks by enabling the native-born workers to move into jobs that could be undertaken from the safety of their homes or with lower face-to-face interactions. The effects on the native-born population are more pronounced for high-skilled workers than for low-skilled workers, and for women than for men. We do not find significant effect of immigration on

wages and employment—indicating that the effects are mostly driven by a reallocation of natives from less safe jobs to safer jobs.

KEYWORDS

COVID-19 pandemic, immigration, labor market vulnerability, occupational choice

JEL CLASSIFICATION

F22, J28, J61

1 | INTRODUCTION

COVID-19 pandemic continues to expose almost everyone in the world to unforeseen health and economic risks. This article explores the ways in which the prevalence of immigration in a labor market affects different types of workers' exposure to these risks. We provide evidence that not only the immigrant workers were more exposed to the economic and health-related shocks of the pandemic, but they also served as a protective shield to the native workers. By selecting into higher risk occupations, immigrants enable the native workers to move into jobs that can be undertaken from the safety of their homes or with lower face-to-face interaction with customers and co-workers.

The findings come in contrast to the political narrative prevailing in the main high-income destination countries at the beginning of 2020. The United Kingdom completed its withdrawal from the EU on January 31, 2020, in part due to the desire to have more control over its immigration policies and limit migrants' flows. Intense political debates and polarization on immigration partly fueled the rise of the right-wing parties in Europe and the political controversies over the border wall or the Dream Act in the US. Despite these high-profile examples of the popular and political backlash against immigration, the academic literature provides ample evidence on how immigrant workers often fill the difficult and dangerous jobs that locals are not willing to undertake (Orrenius & Zavodny, 2009, 2013; Sparber & Zavodny, 2021). As this article shows, COVID-19 provides another example where immigrant workers are, in effect, "protecting" the native worker by virtue of taking on the jobs that turn out to be the riskiest during the pandemic.

Different types of workers sort into different types of jobs according to their abilities, preferences, educational attainment levels, age, and other personal characteristics. These distinctions are especially pronounced between native and immigrant workers. Immigrants face additional sorting mechanisms that define and constrain their occupational choices: they are affected by legal constraints, immigration networks, educational downgrading, limited language skills, and limitations on the recognition of their foreign qualifications.¹ In response to the arrival of immigrants, native-born workers may leave certain geographic areas, occupations or sectors, and enter other markets to better exploit their comparative advantages (World Bank, 2018). Such endogenous (and pre-pandemic) location and occupation decisions of both immigrants and natives shape their relative exposure to and the impacts of the labor market and health shocks created by both the pandemic itself and government measures to control its spread. The empirical analysis in this article accounts for these endogenous decisions while quantifying different types of workers' health and economic exposure to COVID-related risks.

A critical feature of the COVID-19 pandemic is that it generated simultaneous supply and demand shocks that rapidly increased unemployment levels, health risks, and income losses. On the supply side, many sectors faced various disruptions, resulting mainly from mobility restrictions and closures that governments continue to impose to control the spread of the epidemic. Many sectors experienced severe contractions that were most pronounced for occupations that were *not* deemed essential, and for tasks that could not be performed from home. On the labor-demand side, unemployment and earnings losses have been widespread, due to sudden declines in overall economic activity, especially in sectors related to transportation, tourism, restaurant and food services, direct retail and personal services. Demand growth in sectors such as health care or Internet retail has failed to compensate for these losses in other sectors. In addition, workers in many occupations face health risks from direct exposure to potentially infectious people with whom they interact in the course of their work. This is a vital concern for essential occupations that cannot be carried out from home and require extensive and hard-to-avoid face-to-face interactions with customers or coworkers. Many jobs in retail, health, and education fall into this category.

To assess the exposure of immigrant and native workers to the economic and health risks posed by the pandemic, we construct various measures of vulnerability. We first show that immigrants are generally employed in occupations that are more vulnerable to these COVID-19-related risks. We then examine whether the presence of immigrants in local labor markets impacts the vulnerability of native workers in the same geographic areas. Our empirical analysis is motivated by a general equilibrium model of comparative advantages in task performance between immigrant and native workers (Peri & Sparber, 2009). In the model, native workers reallocate to other occupations in response to an influx of immigrant workers. We use a Bartik-type of instrument to account for the endogeneity of migrants' location choices that respond to local job opportunities. We focus on destination countries in Western Europe, including the 15 countries that were the initial members of the European Union (prior to the 2004 enlargement), Norway, and Switzerland. This region is the destination for an estimated 60 million of some 272 million immigrants worldwide. The analysis is based on a harmonized labor force dataset that contains detailed information on personal characteristics (such as age, education, occupation, and sector) of native workers and labor migrants in hundreds of local labor markets in subregions within European countries.²

We find that native-born workers in European subregions that have a higher share of immigrants are significantly less likely to be exposed to various dimensions of occupational vulnerability associated with COVID-19. We show that the relationship is causal, and results get stronger once the endogeneity of immigrants' location choices is taken into account. We also find heterogeneous effects depending on characteristics of native workers. The effects of immigration on job safety are stronger for highly (tertiary) educated native workers, who benefit from the presence of both high-skilled and low-skilled migrants. By contrast, the effects are smaller and statistically insignificant for less (non-tertiary) educated native workers. We also assess whether these compositional effects on employment of certain types of native workers are accompanied by effects on their total employment and wages. We find no evidence of wage or employment impacts among native workers, suggesting that the increase in job safety among native workers is driven by their reallocation from vulnerable jobs to safer jobs. In short, we show that immigration to Western Europe reduced the economic exposure of native-born workers to some of the COVID-19-related labor market shocks by pushing them into occupations that are more amenable to working from home.

The literature on the labor market impact of the COVID-19 pandemic has grown exponentially over a very short period. As these papers all show, the impact of COVID-19 on labor markets

has been very profound, with asymmetric effects across occupations and population groups (see, e.g., Adams-Prassl et al., 2020; Béland et al., 2020; Coibion et al., 2020). Several studies indicate that the employment risks associated with COVID-19 disproportionately affect workers who were already exposed to wage and job uncertainties prior to emergence of the pandemic (Casarico & Lattanzio, 2020; del Rio-Chanona et al., 2020; Mongey et al., 2021; Papanikolaou & Schmidt, 2020; Yasenov 2020). Similarly, Garrote-Sanchez et al. (2021) show that COVID-19 is likely to exacerbate inequality between workers—especially in richer countries, where better paid and better educated workers with secure jobs are more insulated from the shock. Using monthly data in the US for 2020, Montenegro et al. (2020), Liu and Mai (2020), and Cajner et al. (2020) show occupations that require greater physical proximity and less suitability for teleworking exhibited larger employment losses.

By focusing on another category of vulnerable workers—immigrants—our article contributes to the recent literature on the occupational exposure to COVID-19 related risks. The handful of papers specifically comparing the COVID-19 exposure of immigrant and native workers finds that immigrant workers are typically more exposed to both economic and health shocks associated with the pandemic (Basso et al., 2020; Fasani & Mazza, 2020a, 2020b; Yasenov 2020). Among the reasons proposed by Borjas and Cassidy (2020) is the higher concentration of migrants in jobs with lower potential to be performed remotely. Yasenov (2020) finds that only 30% of the migrants in the United States have jobs suitable for telework, compared to 45% of natives. While these papers compare migrants and natives, the impact of immigrants on native workers' economic and health exposure to the COVID-19-related shocks—the causal linkages—have not yet been fully explored to the best of our knowledge.

Although our article focuses on health and economic vulnerability in the context of the COVID-19 shock, it also contributes to the broad and older literature on the general relationships between immigration and natives' occupational choices, especially in jobs less prone to negative economic shocks. Studies published before the COVID-19 pandemic suggest that immigration tends to push natives towards better jobs in the US. Peri and Sparber (2009, 2011) show that immigration pushes natives away from manual occupations into occupations that require more communication-intensive skills, since they have comparative advantage in these areas. Dillender and McInerney (2020) show that Mexican immigration leads US natives to move into safer jobs. Bond et al. (2020) find that immigration leads US natives to move away from shift work into daytime jobs. Orrenius and Zavodny (2009) and Sparber and Zavodny (2021) show that migration to the US leads less-educated native-born workers to move into jobs with less exposure to hazardous conditions, and that those effects are stronger for female native workers. D'Amuri and Peri (2014) and Foged and Peri (2016) extend the analysis for Europe, again presenting evidence that immigrants, by taking manual occupations, push natives towards more abstract and communication-intensive jobs. Alacevich and Nicodemo (2019) show that inflows of foreign-born workers drive reductions in the injury rate, paid sick leave, and severity of impairment for natives in Italy. In the United Kingdom, Giuntella et al. (2019), find that, in response to migration inflows from 2003 to 2013, medium-skilled, native workers reallocated towards occupations with a lower injury risk index score and lower physical burdens. In Spain, Bellés-Obrero et al. (2021) show that Spanish-born workers are shifting away from manual occupations to those involving more interpersonal interactions.

The remainder of this article is organized as follows: Section 2 describes our conceptual framework. Section 3 discusses the data and methods used to measure economic exposure to COVID-19. Section 4 presents our identification strategy and empirical estimation. Section 5 reports and discusses our empirical results. Section 6 concludes.

2 | CONCEPTUAL FRAMEWORK

Our analysis builds on the highly influential contribution of Peri and Sparber (2009) who provide a simple and intuitive conceptual framework to explore natives' occupational choices in response to immigration. Their model is built around constant elasticity of substitution (CES) assumptions under which native-born and immigrant workers are imperfect substitutes within each skill or education category. In turn, these skill categories are imperfect substitutes for each other in the production of goods and services. In this setting, immigrant workers have a comparative advantage in occupations that require manual tasks, as compared to native-born workers who have relatively better communication and language skills. Communication-intensive tasks are defined as activities such as directing, training, and organizing people; "non-communication/manual" tasks refer to physical skills such as dexterity or strength. As a result of the imperfect substitutability between native and foreign workers, increased immigration causes natives to specialize in language-intensive jobs. In addition to labor specialization, wage effects emerge, showing that compensation for manual tasks declines relative to communication tasks, reducing (and possibly fully compensating for) the adverse wage effects of immigration on native-born workers.

Native-born workers' task specialization (in response to immigration) *prior* to the pandemic can have implications for the exposure of natives and immigrants to labor market risks *after* the pandemic begins to spread. In other words, *ex-ante* (pre-COVID-19) labor market forces arising from immigration may have prompted natives to specialize in and move to occupations that also happen to be less economically exposed to *ex-post* (post-COVID-19) risks that we describe in the data section below. Occupational characteristics that became critical in determining unemployment risks during the COVID-19 pandemic could not have been foreseen prior to the outbreak.³ However, pre-pandemic occupational choices of migrants are linked to high-risk occupational exposure to the pandemic (Bossavie et al., forthcoming). As migrants concentrate in high COVID-19-risk occupations, natives' risk levels would be expected to fall. This would arise, for example, if natives were pushed (or encouraged) to move to higher-skilled occupations that also turned out to be more amenable to home-based work once the COVID-19 shocks hit.

We use the relative task content of jobs to construct different types of risks that arise due to the pandemic (Section 3). We then identify the correlation between the relative intensity of manual and communication tasks that different occupations entail with the exposure risks of occupations. This approach allows us to link Peri and Sparber's conceptual framework directly with measures of labor market vulnerabilities created by COVID-19 related risks.

3 | DATA AND DESCRIPTIVE STATISTICS

3.1 | Data

The primary data source used throughout this article is the European Labour Force Survey (EU-LFS), which is a harmonized dataset composed of nationally representative labor force surveys conducted in all of the 28 EU countries, in addition to Switzerland and Norway. The sample size of the EU-LFS ranges from 4.5 million to 5.2 million observations depending on the year. Data are available on a yearly basis between 2001 and 2018, the latest available year prior to COVID-19. The data provide information on whether the individuals in the sample were born in the same country in which they work. While the specific origin countries of migrant workers are not available in the data, broad world regions of origin are observed. These are as follows: the 15 original

member states of the European Union (EU15),⁴ the 13 new member states of the EU as of 2013 (NMS13),⁵ non-EU European countries, Latin America, Asia, the Middle East and North Africa, Sub-Saharan Africa, and other non-European high-income countries that are members of the Organization for Economic Co-operation and Development (OECD).⁶

The dataset includes detailed information on various labor market outcomes of the individuals sampled, along with their demographic characteristics such as gender, age, and educational attainment. In terms of labor market status, observations are labeled as (i) out of the labor force, (ii) seeking employment, or (iii) currently employed. Detailed information on the characteristics of the jobs of employed workers are classified according to (1) the sector of activity at the one-digit disaggregated level of the Statistical Classification of Economic Activities in the European Union (NACE); and (2) by occupational categories up to the three-digit level of the International Standard Classification of Occupations (ISCO-08). Because the ISCO classification scheme changed significantly between 2010 and 2011,⁷ we restrict our final sample to the period from 2011 to 2018. In addition, the dataset includes information on the wage decile of the worker in the national wage distribution for individuals who are wage employees.⁸ Finally, the dataset provides information for each observation within destination countries at a subnational, regional level: the European Commission's second level of nomenclature of territorial units for statistics (NUTS2). This allows us to measure immigrants' presence and labor market outcomes at a rather disaggregated geographical level, and to conduct our estimation at the regional level within European countries. For our analysis, we restrict the sample to the 124 NUTS2 regions in Western Europe, which includes the EU15 countries, Switzerland, and Norway. The share of migrants in the New Member States (NMS13) countries is very small, so the sample captured in the EU Labour Force Survey (EU-LFS) can be noisy.

3.2 | Measuring economic and health exposure to COVID-19 and correlation with the task content of occupations

Labor-force surveys are not yet available to provide post-COVID-19, harmonized information of labor-market outcomes for the European Union, at the sub-region level. We categorize economic exposure to COVID-19 using information on workers' occupations and labor market outcomes *prior* to the pandemic. This approach reflects the method used in the literature (e.g. Dingel & Neiman, 2020; Garrote-Sanchez et al., 2020) to measure risk exposure before an event takes place. We observe the detailed occupational categories in the data, including the three-digit ISCO-08 categories, which we use to estimate the economic exposure of different types of workers to COVID-19.

We use four different metrics of vulnerability throughout this article to assess occupation-specific exposure to the COVID-19 risks. These metrics address the definition of essential workers, the ability to work at home, the degree of income safety, and the extent of health risk. The first three measures capture the effects of supply side shocks while the fourth is directly related to exposure to infection. The measures are defined as follows:

1. *Essential workers*: We define jobs as essential if they are exempt from mobility restrictions even in the presence of government mandated lockdowns. When categorizing jobs as "essential," we follow Fasani and Mazza (2020a) who use the European Commission's guidelines concerning the exercise of the free movement of workers during COVID-19 outbreak in the first half of 2020,⁹ and supplement it with the Dutch government's definition of "key

workers.” Throughout this uncertain period, governments provided lists of occupations considered essential and thus exempt from mobility restrictions and closures during lockdowns. While the criteria for essential occupations vary somewhat from country to country, there is a significant overlap, such as core occupations delivering critical health care (doctors, nurses, and other medical professionals) and providing basic goods and services (food, utilities, transport, security, ICT, or research and science). Based on these criteria, we categorize jobs at the three-digit ISCO-08-classification level (which includes 182 occupations) as either essential or nonessential. According to this definition, about 37.8% of the working-age population in the EU works in occupations that are deemed essential.¹⁰

2. *The ability to work from home*: Our “amenability to home-based work” metric is based on the premise that a person faces lower employment and income risk if she can work at home, and higher risk if she is required to be physically present in the workplace to carry out the required tasks. Recent literature on the impact of COVID-19 on labor markets highlights the feasibility of home-based work (telework) as a key determinant to overcome governments’ mobility restrictions and associated income and/or unemployment risks. The ability to telework also limits the exposure to health risks among workers that face supply shocks. Dingel and Neiman (2020) use the Occupational Information Network (O*NET) surveys to calculate the amenability of different occupations to telework in the United States, including questions such as the importance of the use of email, the frequency of operating and handling big machinery or processes, or performing physical and outdoor activities. Dingel and Neiman’s (2020) measure, however, is based on the Standard Occupational Classification (SOC) system used in the United States at a very granular (6-digit) level of disaggregation. We then concord and aggregate this classification to the International Standard Classification of Occupations (ISCO08) at the 3-digit level, which is widely used in the analysis of EU labor markets. The final measure used in the empirical analysis, a continuous variable between 0 and 1, is the weighted average of occupations in each ISCO 3-digit category that are amenable to telework. As Dingel and Neiman (2020) acknowledge, their Home-Based Work (HBW) index is likely to represent an “upper bound” on the number of jobs that could feasibly be performed entirely from home, as it “neglects” many characteristics that would make working from home difficult.
3. *Income safety*: This metric characterizes the degree of income safety of the job and is a combined index of our first two measures described above. It takes the value of one if the job is essential (shielded from all mobility restrictions) based on our first metric. If the job is not deemed essential by the government, then it is income-safe only to the extent that it can be performed from home (based on the second metric). So, for nonessential jobs, this measure is equal to the measure of amenability to telework for nonessential jobs.
4. *Exposure to health risks*: This measure characterizes the health risks involved in the performance of the tasks entailed by an occupation. It quantifies the extent to which a given essential job (one that is exempt from mobility restrictions) involves face-to-face interactions with clients, co-workers or suppliers. When assessing occupation-specific exposure to health risks, we quantify the extent of face-to-face (FTF) interactions with customers, co-workers and suppliers.¹¹ Our measure of health-safe jobs is a continuous variable between zero and one. It takes the value one if jobs are nonessential. Otherwise, the value varies depending on the amenability to telework (higher levels are associated with higher health safety) and the intensity of face-to-face interactions (higher levels are associated with lower health safety). To quantify the latter, we use the index based on O*NET surveys of task descriptions created by Avdiu and Nayyar (2020).

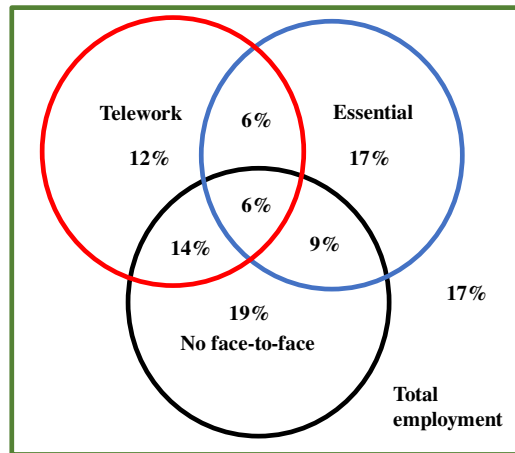


FIGURE 1 Relative size of telework, essential and non-face-to-face jobs in EU-LFS. *Source:* Own elaboration based on EU-LFS data (2018) and O*NET surveys (2019)

The relationships between these four measures and the share of workers in the labor force who fall into each category are shown in Figure 1. For example, 38% of the workers in our sample are considered essential (Measure #1—blue circle). Similarly, 38% of the workers are able to work from home (Measure #2—red circle). Some 12% of these teleworkable and essential jobs overlap, which means 64% of the workers in our sample have “income-safe” jobs (Measure #3—combined area of blue and red circles). We find that 48% of the jobs do not require face-to-face interaction (black circle). An estimated 15% of these jobs are also essential, and 20% are telework jobs. In total, 17% of all jobs are exposed to health risks (Measure #4—area of the blue circle that does not overlap with either of the red or black circles). These are the essential jobs that require face-to-face interaction but cannot be performed from home via telework. In our sample, 6% of jobs can be considered the “best” jobs with the minimal economic and health risk exposure to COVID-19. That is, they are essential, can be done from home, and do not require face to face interaction. These jobs fall into the overlap of the three circles. By contrast, 17% of the jobs (those outside the three circles) can be considered to have the highest risk level. These jobs are nonessential, cannot be done from home, and require extensive face-to-face interactions.

The measures of income safety by occupation are strongly correlated with the relative task content of those occupations, as shown by the literature (Autor & Handel, 2013; Autor et al., 2003). To calculate the task content of a given occupation, we use the US Department of Labor O*NET abilities survey, which provides information on various characteristics of occupations. We follow the same “basic” definitions of manual and communication skills used in the literature. We thus define manual tasks as those that require “movement and strength,” and we define communication tasks as those that require oral and written expression and comprehension. We then determine the extent to which various jobs entail such tasks by merging these measures with the EU-LFS data and constructing concordances between SOC and ISCO categories of occupations.

There is a strong and positive correlation between the relative intensity of communication and manual tasks required in occupations and the share of teleworkable jobs (our Measure #2) at the three-digit ISCO level (Figure 2). The Pearson correlation coefficient is 0.87 and statistically significant at the 1% level. As the O*NET survey shows, jobs classified as teleworkable also tend to require a higher intensity of communication-oriented tasks. The correlation between income-safe jobs (teleworkable *or* essential) and the relative share of communication to manual

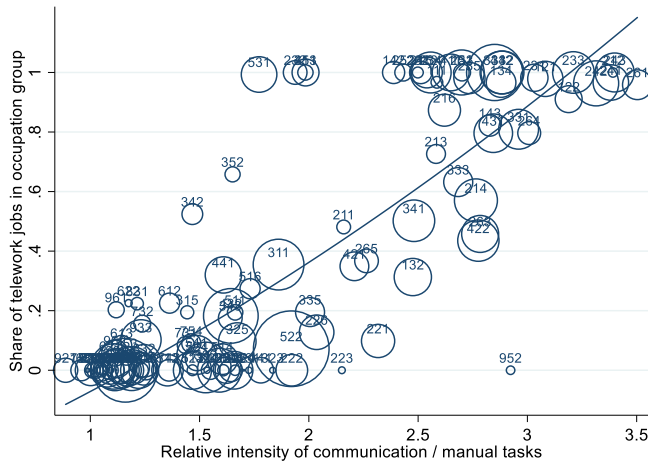


FIGURE 2 Correlation between the relative intensity of communication versus manual tasks and the share of teleworkable jobs in each of ISCO three-digit occupations in 2018. The size of the circles represents the relative size of each ISCO three-digit occupation in employment. The correlation uses the relative size of each occupation as weights. *Source:* Own elaboration based on EU-LFS data and O*NET surveys

tasks is also positive, although slightly weaker than for telework jobs alone.¹² This is due to the fact that certain essential jobs, such as low-skilled delivery jobs, require fewer communication tasks. Similarly, there is also a positive correlation between health-safe jobs and the relative share of communication tasks.¹³

3.3 | Migrant-native gaps in income and health risk exposure to COVID-19

Before illustrating the econometric analysis, we present several descriptive statistics of our sample of working age individuals (ages 25–64) from the EU Labour Force Survey. As of 2018, there were 270 million working-age people residing in Western European countries. Almost one out of five (18.7%) of them were foreign-born (Table A1 in the Appendix). These immigrants originally come from various high-income Western European countries (3.1%), new EU member states such as Poland and Romania (3.6%), other European countries that are not EU members (3.5%), and other locations outside of Europe (8.1%). Migrant workers are slightly younger than native workers on average (mean age is 43 vs. 45.4) and have a slightly lower share of men than the native workforce (48.4% vs. 50.2%). Migrants also have slightly lower education levels, with 31.2% having tertiary education degrees compared to 33.5% of natives. There is, however, significant variation with respect to education levels depending on migrants' region of origin. The share of workers with tertiary education is higher among immigrant workers from other EU15 countries (43%) compared to those from non-EU European countries (21.2%) and new EU member states (27.3%). Female migrants to the EU also tend to be more educated than male migrants (32.3% vs. 30.0%), especially among migrants from non-EU European countries and new member states.

The employment rate of immigrant workers in the EU is significantly lower than that of natives, both for high-skilled and low-skilled individuals (Table A2 in the Appendix). Among immigrant workers, 70.7% are employed, 9.0% are unemployed, and the remaining 20.3% are out of the labor force. The corresponding figures for native-born workers are: 77.6% employed, 5.4%

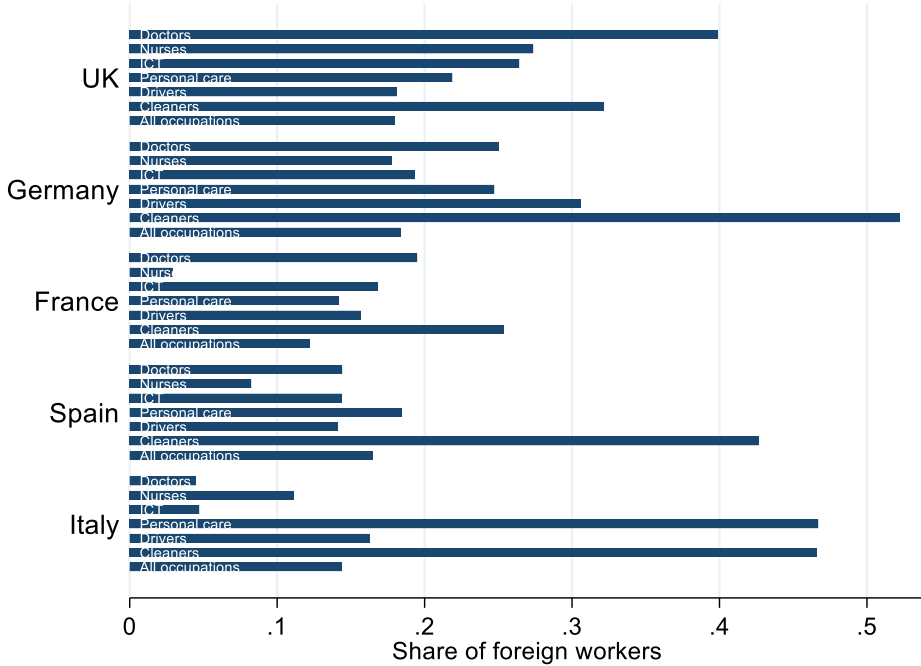


FIGURE 3 Share of foreign workers in key essential occupations by destination country. *Source:* Own calculations based on EU-LFS 2018 data

unemployed, and 17% out of the labor force. Among the tertiary educated, employment levels are 79.2% for immigrants and 87.5% for native workers. Employment figures decline significantly for less-educated groups, to 67% for immigrants and 72.6% for natives. The main contributor for the employment gap is the lower labor force participation rate of immigrant women (see Table A4 in the Appendix).

Pre-COVID occupational decisions of migrants or natives were not shaped by concerns about economic vulnerability in a future pandemic since COVID-19 was a true shock in the econometric sense. Yet, we still observe significant and systematic differences in economic exposure to COVID-19 related risks. Among the employed, we observe significant differences in the types of jobs immigrant and native workers have. For example, 27.3% of immigrant workers are employed in teleworkable jobs compared to 40.9% of native-born workers. This difference is also observed when we compare natives and migrants within the same education group. Immigrant workers, however, are more likely to be employed in essential jobs (41.8%) compared to natives (37.6%). Although the share of essential jobs varies across destination countries, migrants are over-represented in essential jobs in almost every host country in the EU15. Essential jobs tend to be concentrated among highest- and lowest-skilled occupations (such as physicians and grocery store employees) both for natives and immigrants. As seen in Figure 3, immigrant workers in Western European countries represent a very large share of essential workers in the health sector, specifically among doctors and nurses, as well as ICT. However, the share of immigrant workers is even larger in essential jobs that also have the lowest wages and the lowest levels of education. We find that 40.4% of migrants with low levels of education have essential jobs, compared to 34.1% of native workers. Finally, immigrants are less likely to be employed in income-safe jobs (53.9% vs. 65.3% of native workers) and in health-safe jobs (77.1% vs. 84.4%) though the difference between the immigrants and the natives is narrower in the latter (84.4% vs. 77.1%).

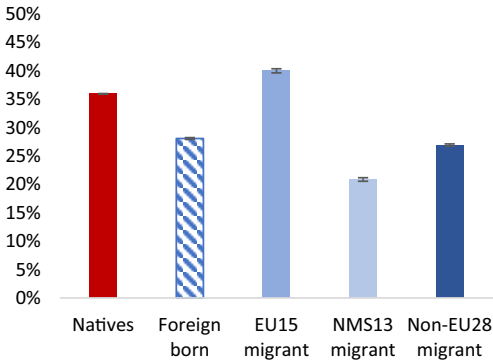
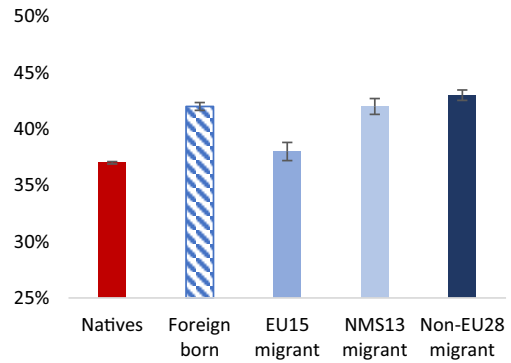
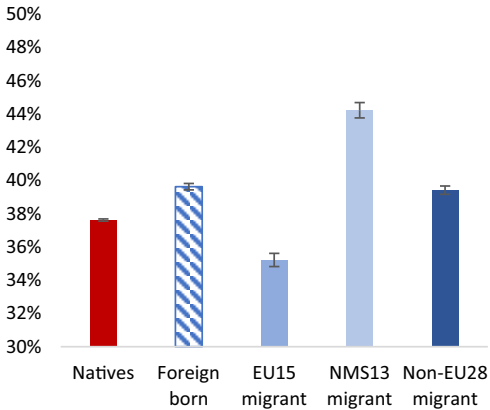
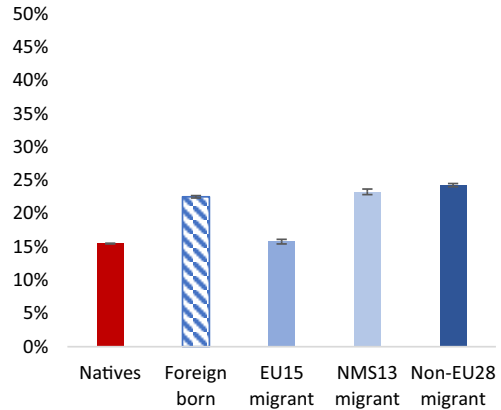
Panel A. Telework jobs**Panel B. Essential jobs****Panel C. Income risk jobs****Panel D. Health risk jobs**

FIGURE 4 Share of workers by region of origin and risk type. *Source:* Own calculation based on EU-LFS 2018 data, following EC directive (2020) and Fasani and Mazza (2020b)

Figure 4 highlights the heterogeneity in exposure to labor market risks between immigrants from different regions of the world, especially between migrants from high-income EU15 countries relative to the rest of immigrants. For telework jobs, the share of immigrant workers from EU15 countries is even higher than natives' share, whereas it is significantly lower among migrants from NMS13 and non-EU countries (Panel A). While the share of immigrant workers in essential jobs from NMS13 countries and the rest of the world is significantly higher than it is for native workers, the share of migrants from other EU15 countries in those jobs is very similar to the share for natives (Panel B). Likewise, the share of EU15 migrants exposed to income risks is lower than the share of natives, while it is significantly higher for migrants from other parts of Europe or the rest of the world (Panel C). Regarding health risks, migrants from EU15 countries are exposed to the same level of risk as natives, while migrants from other regions are significantly more exposed (Panel D).

We observe significant differences in exposure to economic and health-related risks associated with COVID-19 between male and female migrants. Women, both native-born and immigrants,

are more often employed in teleworkable jobs compared to men (Table A4 in the Appendix). This pattern is mainly driven by women with low levels of education who are more likely to be in teleworkable clerical or office-based occupations; by contrast men of similar education levels tend to be employed in manufacturing-oriented or menial jobs. The shares of male and female workers with high levels of education in teleworkable jobs are about the same, regardless of whether they are immigrants or native-born.

The share of male and female native workers in essential jobs is about the same (37%); however, the share of female migrants in essential jobs (47.8%) is much higher than male migrants (36.9%). This pattern is again driven by less-educated workers. We see that 50.4% of female migrants with low levels of education are in essential jobs, compared to 32.8% of male migrants with low levels of education. Female migrants are also more likely to be in income-safe jobs (68.6%) compared to male migrants (51.6%). A similar pattern is observed among native workers, although the gap is less pronounced. These gender patterns are again driven by low-skilled migrants. Our data show that 63.4% of female migrants with low levels of education are employed in income-safe jobs compared to only 40.7% of male migrants with similarly low levels of education. On the other hand, female migrants are much less likely to be employed in health-safe jobs (66.7%) compared to male immigrants (85.7%) or female natives (79.7%).

Income levels also show variation by origin and education levels. Unfortunately, the survey only reports the income decile of a worker (within a country) rather than an exact income level. Hence, our analysis is less precise. Migrant workers are less likely to be in the top three wage deciles (24.4%) compared to natives (35%) (Table A3 in the Appendix). This income gap between natives and immigrants is observed for workers with both high and low levels of education. For example, 47.1% of immigrant workers with tertiary education are in the top three deciles, as opposed to 57.4% of native workers with a similar education level.

The highest wages are observed among workers in teleworkable jobs. We find that 47.7% of all workers with teleworkable jobs are in the top three deciles. This ratio is almost identical between migrant and native workers. For other types of jobs, however, the wage penalty of immigrant workers is much more salient. An estimated 37.2% of natives in essential jobs are in the top three deciles, compared to 23.2% of migrants in the same types of occupations. For income-safe jobs, the proportion is 40.3% for natives compared to 28.7% for immigrant workers. The pattern is similar for health-safe jobs.

Significant wage gaps are also observed between male and female workers, regardless of education level and migration status. 47% of male native workers are in the top three income deciles, compared to 22.4% of native women (Table A5 in the Appendix). Among migrants, 32.6% of men and only 14.8% of women are in the top three deciles. These significant gender wage gaps exist among workers (regardless of education or migration status) in teleworkable jobs, essential jobs, and income-safe jobs. For example, 55.8% of native males in income-safe jobs are in the top three deciles, compared to 26.6% of native women. Among immigrants, 41.1% of males in income-safe jobs are in the top three deciles, compared to 18% for immigrant women.

4 | EMPIRICAL STRATEGY AND IDENTIFICATION

We now investigate whether immigration to high-income Western European countries had a causal impact on the extent of exposure of native workers to COVID-19-related economic and health risks via the jobs they hold. As discussed above, our empirical specification to study this question is derived from the conceptual framework of Peri and Sparber (2009). A critical issue to

identify causal effects in this context is that the employment of migrants in specific geographic regions or in specific occupations is likely to be endogenous, driven by market conditions, expectations, social networks, and historical precedents. This section discusses the empirical strategy used to address such selection biases.

We first construct measures of different types of risks (at the NUTS2 level) to which native workers are exposed, based on their occupations. Since the analysis is at the regional level, we first must control for differences in terms of the distribution of workers by their education, gender, and age. This step is necessary because those personal characteristics affect the supply of skills required for different types of occupations, and, at the same time, they may be correlated with the size of immigration in the region. To control for this spurious correlation, we first run individual-level regressions to predict how occupation- and labor-market-related characteristics for each individual i depend on individual observable characteristics. We perform these regressions separately for each of the years of study (2011–2018) and by immigration status (native vs. migrant):

$$Status_i = a + b * X_i + e_i. \quad (1)$$

$Status$ stands for each of the main six variables capturing natives' and migrants' status in the labor market. The first four are occupation-level measures defined in the previous section: essential jobs (Measure # 1); amenability to telework (Measure #2); degree of income-safety (Measure #3); or health-safety (Measure #4). The last two are dummy variables based on the employment status (employed or unemployed) or the income level (in the top three income deciles) of the individual. X_i is a vector of individual-level characteristics such as gender, education, and dummies for age groups. Using this measure, we calculate the gap between the actual measure and the predicted one (\widehat{Status}_i) for each individual based on the estimated parameters:

$$g_Status_i = Status_i - \widehat{Status}_i, \quad (2)$$

where $\widehat{Status}_i = E[Status_i | X_i] = \hat{a} + \hat{b}X_i$. This gap is a measure of each of the main six labor-market outcomes of interest “cleaned” of differences in individual level characteristics. We then calculate the *weighted mean* of the variable g_Status_i across individuals in each NUTS2 region. The weights used are the individual weights in the EU-LFS sample multiplied by the number of hours worked in a week.

The obtained variable, now denoted g_Status_{st} for each region s and year t , becomes the dependent variable in our estimation framework, which we regress on the fraction of migrant workers in the working-age population in region s and year t (f_{st}), together with region and time fixed effects. The baseline equation we estimate is given therefore by the following:

$$g_Status_{st} = \gamma f_{st} + \alpha_s + \tau_t + \varepsilon_{st}. \quad (3)$$

In this specification, g_Status_{st} is the adjusted measure of risk exposure among the working-age population of natives in NUTS2 region s and year t ; τ_t are the time fixed effects that account for common, time-varying technological parameters; α_s are region fixed effects that account for variation due to time-invariant unobserved characteristics of the population in that region; and f_{st} is the share of foreign workers in each region and year. Therefore, γ is the main parameter of interest in the estimation. From the EU Labour Force Survey, our sample consists of 123 NUTS regions in 14 EU countries observed with yearly frequency from 2011 to 2018.

Estimating Equation (3) using a standard OLS approach can raise endogeneity concerns, even after including fixed effects to control for unobserved regional characteristics and time patterns. In particular, OLS estimates for γ may be inconsistent if the share of immigrants in EU regions is correlated with the unobservable term in Equation (3) (i.e. $E[\varepsilon_{st}|f_{st}] \neq 0$). This might arise, for instance, when migration flows to a given region are driven by unexpected contemporaneous region-specific shocks. Further, OLS estimates could suffer from reverse causality if migrants choose to locate in areas where natives are employed in occupations that complement migrants' skills. These occupations, in turn, may differ in their degree of exposure to economic and health risks due to COVID-19. Similarly, unobserved technology and demand shocks, which may differ across EU regions due to sectoral variation, may simultaneously affect the productivity of (and demand for) certain occupations as well as the demand for immigrant workers. A large body of literature indeed shows that migrants' location choices are endogenous with respect to local labor market conditions, including native workers' characteristics and labor market outcomes (World Bank, 2018). Therefore, OLS estimates of the relationship between the vulnerability of the jobs that natives hold to COVID-19 and the degree of presence of immigrants in the region may not reflect true causal effects.

We use an instrumental variables (IV) approach to address the possible endogeneity of the share of migrants in a given destination region. We follow a consolidated approach in the literature and construct a shift-share Bartik instrument to control for the current migrants' share in a given region.¹⁴ The instrument consists of both a "share" and a "shift" component. To build the instrument, we use the spatial distributions of immigrants in 2002 across European NUTS regions (the initial "share" prior to the period of analysis), interacted with the aggregate growth rate of the stock of immigrants at the EU level between 2002 and the year of study (the "shift").¹⁵ The "share" component provides predictive power to the instrument. It relies on the fact that new immigrants' settlement decisions are partly determined by the presence of earlier immigrants, mainly through network externalities (Gross & Schmitt, 2003). Recent migrants learn of opportunities in those locations from the network of immigrants, and they may prefer the benefits of living near their co-nationals.¹⁶ As a result, the past distribution of immigrants across European regions can help predict their current location. The "shift" component provides exogeneity to the instrument if the events influencing the flow of migrants to the EU as a whole are arguably exogenous to changes to the labor market conditions in each NUTS region. These criteria will be satisfied as long as each region is small relative to the EU and business cycles of the regions are not highly correlated.

Formally, our first Bartik instrument—denoted PS, hereafter—for the share of immigrants in each region can be expressed as the following:

$$Pct_mig_{st} = Share_mig_{s,2002} * \left[\frac{(1 + g_{mig})_{t,2002}}{(1 + g_{nat})_{t,2002}} \right], \quad (4)$$

where $Share_mig_{s,2002}$ is the share of migrants in NUTS2 destination region s in 2002; $(1 + g_{mig})_{t,2002}$ is the growth rate of working-age migrants in EU15 countries between 2002 and year t ; and $(1 + g_{nat})_{t,2002}$ is the growth rate of working-age natives in all EU15 countries between 2002 and year t .

One potential concern with this baseline version of the Bartik instrument is that it uses the contemporary number of native individuals in a given European region. As a result, the instrument may capture spurious effects due to the potentially endogenous native population growth in a destination region—which could be due, for example, to internal labor mobility of native workers in response to local demand shocks. To address this concern, we construct a second version of

the Bartik instrument in which we fix the native population at the initial year (2002, in our case) as suggested in Mitaritonna et al. (2017). We first define:

$$M_{st} = \left(\frac{M_{s,2002}}{M_{eu,2002}} \right) * M_{eu,t},$$

where M_{st} is the number of migrants in time t in destination NUTS2 region s ; $M_{s,2002}$ is the number of migrants in destination region s in 2002; $M_{eu,2002}$ is the number of migrants in the EU15 in 2002; and $M_{eu,t}$ is the number of migrants in the EU15 in year t . Then the instrument for the share of migrants Pct_mig_{st} based on Mitaritonna et al. (2017)—denoted MOP instrument, hereafter—is:

$$Pct_mig_{st} = \left(\frac{M_{st}}{M_{st} + N_{s,2002}} \right), \quad (5)$$

where $N_{s,2002}$ is the number of natives in destination region s in 2002.

The Bartik instrument is valid under the condition that the past migration networks (which create differential exposure to common immigration shocks) do not have a direct effect on natives' occupational choices—such as, in our case, the allocation between jobs that are economically exposed or not exposed to COVID-19 (Goldsmith-Pinkham et al., 2020). In other words, the distribution of immigrants across regions of Europe in 2002 should be orthogonal to subsequent labor market shocks in the region, conditional on region and year fixed effects. Therefore, our identification strategy posits that the reasons to co-locate where previous immigrants lived are driven by preference and information networks, and arguably not by region-specific labor market shocks.

A standard concern in the literature is that the initial distribution of immigrants is correlated with persistent local factors that also influence natives' allocation across occupations. As discussed in Dustmann et al. (2005), Basso and Peri (2015), and Edo et al. (2019), a way to minimize the correlation between past immigration and current outcomes is to use a sufficiently long time lag to predict the actual number of immigrants. To mitigate this concern, we derive initial migration shares using data from 2002—the first year for which data are available in the EU Labour Force Survey, and benchmark time that is 9 years before the beginning of our period of analysis. In addition, we control for region fixed effects that take care of unobservable regional characteristics in the IV specification, to ensure that the exclusion restriction is met.

Another possible concern with the shift-share instrument is that using an earlier distribution pattern of immigrants as an instrument can violate the exclusion restriction in the presence of general equilibrium adjustments and strong serial correlation of immigrant flows (Jaeger et al., 2018). If it takes time for markets to adjust to shocks, the error term can also include other influences that reflect ongoing general equilibrium adjustment effects of past migration shocks. This is a greater concern in contexts where the mix and share of immigrants does not vary much over time, like in the US, and where, as a result, the first stage of the IV estimation is stronger due to more stable migration inflows. As noted by Jaeger et al. (2018), the serial correlation in the number of immigrants is lower in Europe compared to the United States as immigration patterns to Europe have changed substantially over time.¹⁷ In particular, the period between our initial measure of immigrant share in 2002 and our period of study for labor market outcomes, which starts in 2011, has been marked by the EU enlargement which triggered important changes in migration flows to the EU (Elsner, 2013).

A final concern is that the total inflows of immigrants in the EU (the shift) could be correlated with local demand-pull factors, given that the inflows include the immigration growth rates

in the NUTS2 region of reference. To mitigate this issue, prior studies have adjusted the measure of the exogenous supply-push factor by using migration flows to destination areas other than the one of reference (Ajzenman et al., 2021). As a robustness check, we adjust the PS and MOP instruments including just the growth rate of immigration to all EU NUTS2 regions besides the one of analysis in the “shift” component. Our main results are robust to this alternative instrument, although the instrument becomes slightly weaker (as measured by the F-stat of excluded instrument).¹⁸

5 | RESULTS

5.1 | Impact of immigration on occupational exposure to COVID-19

We now report our results on the impact of the extent of immigration across EU regions on several dimensions of occupational exposure to the COVID-19 pandemic, based on the data and empirical approach detailed in Section 3. The first indicator of occupational safety with respect to COVID-19 exposure is the share of natives employed in teleworkable jobs (i.e. those jobs that can be carried out from home—our Measure #1). The first three columns of Table 1 display the naïve OLS estimates for the effects of the immigrant share on this measure. We observe a large, statistically significant, and positive association between the share of immigrants in EU regions and the share of natives employed in teleworkable jobs. The magnitude of the coefficient implies that an increase of 1 percentage point in the share of immigrant workers in a given region increases the share of natives employed in teleworkable jobs by around 0.25 percentage points. The magnitude of the coefficient is reduced to 0.13 when region fixed effects are also included (column 3), but the estimate remains highly statistically significant.

To address the endogeneity concerns outlined in Section 4 regarding the dependent variable in the naïve OLS estimation, we present our IV estimates of the effect of migrants on natives' share in teleworkable jobs (columns 4–9 in Table 1). The first stage results of the IV estimation are reported in the top panel. The F-statistic is larger than the Stock and Yogo (2005) cutoff of 10 in the specification without fixed effects (columns 4 and 7), and with both time effects and country fixed effects (columns 5 and 8). The instrument remains strong in the most restrictive specification that includes both time and NUTS2-level-region fixed effects (columns 6 and 9), and clusters the standard errors at the NUTS2 level, despite the relatively short time period of study. The results suggest that, according to the criteria of Stock and Yogo (2005), both versions of the instrument are powerful enough to explain variation of the share of migrants across regions, and to identify the treatment effect of interest. In all these specifications, the association between the share of immigrants and our network-based instrument is statistically significant at the 1% level, although the coefficient estimate is slightly reduced once we control for NUTS2 fixed effects (columns 6 and 9).

The bottom panel of columns 4 through 9 of Table 1 reports the second-stage results of our IV estimation, using the two alternative instruments. As in the OLS estimation, the share of immigrants in the region has a positive impact on the share of natives employed in jobs that are amenable to telework once the endogeneity of the migrant share is accounted for. The IV coefficient estimates for γ remain statistically significant at the 1% level and are slightly higher than the OLS estimates when we compare columns 4 and 7 to column 1 in Table 1 (or columns 5 and 8 to column 3 in Table 1). The comparison between IV and OLS estimates suggests that OLS estimates are likely to have a downward bias, underestimating the true effect of migrants'

TABLE 1 Impact of migration on the share of natives 25–64 in telework jobs

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	IV-PS	IV-PS	IV-PS	IV-MOP	IV-MOP	IV-MOP
<i>First stage (dependent variable: fborn)</i>									
Shiftshare (PS)		0.932*** (0.082)			1.005*** (0.0671)	0.462*** (0.124)			
Shiftshare (MOP)							0.879*** (0.078)	0.952*** (0.065)	0.701*** (0.181)
<i>Second stage (dependent variable: share of natives in telework jobs)</i>									
Fborn	0.276*** (0.056)	0.243*** (0.052)	0.126** (0.055)	0.286*** (0.056)	0.247*** (0.051)	0.686*** (0.225)	0.290*** (0.056)	0.250*** (0.050)	0.661*** (0.220)
Constant	-0.054*** (0.009)	-0.038*** (0.012)	-0.000 (0.016)	-0.056*** (0.009)	-0.039*** (0.011)	-0.160*** (0.064)	-0.056*** (0.009)	-0.040*** (0.011)	-0.153*** (0.063)
Observations	982	982	982	982	982	982	982	982	982
F-stat (first stage)				130.4	224.6	13.9	125.5	212.2	15.0
R-squared (second stage)	0.236	0.795	0.959	0.236	0.795	0.934	0.235	0.795	0.937
Dep. var. SD	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Country FE	No	Yes	No	No	Yes	No	No	Yes	No
NUTS-2 FE	No	No	Yes	No	No	Yes	No	No	Yes

Note: Dependent variable second stage: “Adjusted” share of natives in telework jobs (% of the total native population 25–64). Explanatory variable second stage (fborn): Share of migrants 25–64 (% of the total population 25–64). Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The “adjusted” share of natives in telework jobs in a given NUTS2 region and year is the share of natives in telework jobs minus the expected share of telework jobs given its individual level characteristics (age, education, gender), so the mean value is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = standard deviation of the dependent variable. Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.** $p < .05$.*** $p < .01$.

TABLE 2 Impact of migration on the share of natives 25–64 in telework jobs by age group

Variable	(12)	(24)	(36)	(48)	(5)	(6)
	Ages 25–34		Ages 35–54		Ages 55–64	
	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP
Fborn	0.789** (0.313)	0.783** (0.311)	0.719*** (0.279)	0.628** (0.290)	0.727** (0.338)	0.729** (0.304)
Constant	–0.145 (0.089)	–0.143 (0.089)	–0.152* (0.080)	–0.126 (0.083)	–0.226** (0.096)	–0.227*** (0.086)
Observations	982	982	982	982	982	982
R-squared	0.912	0.912	0.916	0.921	0.851	0.851
Dep. var. SD	0.075	0.075	0.061	0.061	0.052	0.052
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No
Nuts2 FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: “Adjusted” share of natives in telework jobs. Explanatory variable (fborn): Share of migrants 25–64 (% of the total population 25–64). Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The “adjusted” share of natives in telework jobs in a given NUTS2 region and year is the share of natives in telework jobs minus the expected share of natives in telework jobs in the region given its individual level characteristics (age, education, gender), so the mean value is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS2 level in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

presence on natives’ take-up of teleworkable jobs. One possible explanation for this downward bias is that immigrants locate in areas where there are more manual, blue-collar jobs rather than teleworkable, white-collar jobs for both native and immigrant workers. As a result, not accounting for the systematic selection of migrants into the regions where there is less supply of teleworkable jobs would lead the OLS result to underestimate the true effect of immigration on natives’ likelihood to be employed in such occupations. The difference between the IV and the OLS estimates increases significantly in our preferred specifications in columns 6 and 9 in Table 1 which include year and NUTS2-region fixed effects. Potential explanations might be the weaker power of the instrument when more granular geographical effects are accounted for, as well as the endogenous sorting of immigrant workers into the EU regions. Specifically, the IV estimates shows that a one percentage point increase in the share of migrants in a given region causes a 0.66/0.69 percentage points increase in the share of native workers employed in teleworkable jobs. The effects are quite sizable, given that 41% of natives work in these types of jobs (so it would increase the share of telework jobs among native workers by about 1.5%). Tables 2 and 3 examine the potentially heterogeneous impact of immigration on the share of natives in teleworkable jobs across gender and age groups. In both cases, we observe a positive impact of migrants’ presence across different subgroups of natives. In terms of age groups (Table 2), the effects are broadly similar across age groups, slightly larger for younger workers (aged 25–34) although the differences are not statistically significant. By gender, the coefficient is somewhat

TABLE 3 Impact of migration on the share of natives 25–64 in telework jobs by gender

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Males				Females			
	IV-PS	IV-PS	IV-MOP	IV-MOP	IV-PS	IV-PS	IV-MOP	IV-MOP
Fborn	0.290*** (0.058)	0.565* (0.290)	0.293*** (0.056)	0.526** (0.261)	0.193*** (0.045)	0.814*** (0.214)	0.197*** (0.044)	0.799*** (0.236)
Constant	-0.068*** (0.012)	-0.150* (0.083)	-0.068*** (0.012)	-0.139* (0.075)	-0.008 (0.012)	-0.170*** (0.061)	-0.009 (0.012)	-0.166** (0.067)
Observations	982	982	982	982	982	982	982	982
R-squared	0.743	0.924	0.743	0.926	0.804	0.910	0.804	0.912
Dep. var. SD	0.054	0.054	0.054	0.054	0.058	0.058	0.058	0.058
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No	Yes	No	Yes	No
NUTS-2 FE	No	Yes	No	Yes	No	Yes	No	Yes

Note: Dependent variable: “Adjusted” share of natives 25–64 (either males or females) in telework jobs. Explanatory variable (fborn): Share of migrants over the total working-age population. Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The “adjusted” share of natives in telework jobs in a given NUTS2 region and year is the share of natives in telework jobs minus the expected share of natives in telework jobs in the region given its individual level characteristics (age, education, gender), so the mean is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

larger for female native-born workers than for male native-born workers, although the differences are not statistically significant (Table 3).

Heterogeneous effects are more prevalent across different educational groups within the labor force (Table 4). We split the first stage of the IV specification between the share of migrants with high levels of education in the total population of highly educated workers, and the share of migrants with lower levels of education in the total population with lower levels of education. The instruments are still strong with country fixed effects, although somewhat weaker when NUTS2-region fixed effects are included. The F-statistic for the excluded instrument falls below 10 (between 7 and 8.5), possibly signaling a weak instrument problem. The second-stage results show that the coefficient estimates for γ are large in the case of the impact on highly educated native workers from the presence of immigrants with both high and low levels of education. The magnitude of the coefficient indicates that a 1 percentage point increase in the share of immigrants with tertiary education increases the share of tertiary-educated natives in teleworkable jobs by around 1.5 percentage points. An increase in the number of immigrants with lower levels of education causes highly educated migrants to move to teleworkable occupations at an even higher rate—around 2 percentage points. In contrast, immigration has no significant impact on the native workers with lower levels of education, and we do not see any change in their share of telework jobs. These heterogeneous effects by education level point towards a higher degree of complementarity between immigrant workers and highly educated natives—possibly

TABLE 4 Impact of migration on the share of natives 25–64 in telework jobs by education levels

Variables	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)		(11)		(12)			
	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP		
<i>First stage (dependent variable: fborn)</i>																										
shiftshare_ps2002	0.856*** (0.099)	0.690*** (0.258)	0.955*** (0.073)	0.203 (0.165)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	0.955*** (0.073)	0.203 (0.165)	
shiftshare_mop2002	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	0.576*** (0.205)	0.681*** (0.080)	
<i>Second stage</i>																										
Fborn	0.289*** (0.084)	1.316** (0.553)	0.303*** (0.083)	1.531** (0.632)	0.214*** (0.058)	2.027** (0.792)	0.218*** (0.056)	2.055*** (0.747)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	0.122 (0.266)	0.195*** (0.042)	
Constant	-0.043** (0.017)	-0.330** (0.159)	-0.045*** (0.016)	-0.391** (0.181)	-0.029** (0.013)	-0.535** (0.226)	-0.030** (0.012)	-0.543** (0.213)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	-0.006 (0.076)	-0.034*** (0.011)	
Observations	980	980	980	980	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	
R-squared 2nd stage	0.803	0.851	0.802	0.824	0.813	0.776	0.813	0.771	0.740	0.954	0.740	0.954	0.740	0.954	0.740	0.954	0.740	0.954	0.740	0.954	0.740	0.954	0.740	0.954	0.740	
F-stat first stage	78.6	7.0	73.4	7.0	258.2	7.3	241.2	8.5	258.2	7.3	241.2	8.5	258.2	7.3	241.2	8.5	258.2	7.3	241.2	8.5	258.2	7.3	241.2	8.5	258.2	7.3
Dep. var. SD	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Country FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	
NUTS-2 FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	

Note: Dependent variable second stage: "Adjusted" share of high-educated or low-educated natives 25–64 in telework jobs. Explanatory variable second stage (fborn): Share of high-educated (hs) or low-educated (ls) migrants (% of the hs or ls population 25–64). Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The "adjusted" share of high/low-educated natives in telework jobs in a given NUTS2 region and year is the share of high/low-educated natives in telework jobs minus the expected share of high/low-educated natives in telework jobs given its individual level characteristics (age, education, gender), so the mean is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach as in Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

TABLE 5 Impact of migration on the share of natives 25–64 in telework, essential and income-safe jobs

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Telework jobs			Essential jobs			Income-safe jobs		
	OLS	IV-PS	IV-MOP	OLS	IV-PS	IV-MOP	OLS	IV-PS	IV-MOP
fborn	0.126** (0.055)	0.686*** (0.225)	0.661*** (0.220)	0.080 (0.063)	−0.272 (0.194)	−0.248 (0.216)	0.178* (0.091)	0.364 (0.256)	0.362 (0.275)
Constant	−0.000 (0.016)	−0.160** (0.064)	−0.153** (0.063)	−0.015 (0.018)	0.086 (0.055)	0.079 (0.062)	−0.018 (0.026)	−0.071 (0.073)	−0.070 (0.078)
Observations	982	982	982	982	982	982	982	982	982
R-squared	0.959	0.934	0.937	0.909	0.892	0.895	0.941	0.939	0.939
Dep. var. SD	0.054	0.054	0.054	0.042	0.042	0.042	0.063	0.063	0.063
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No	No
NUTS-2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: “Adjusted” share of natives in each type of occupation (% of the total native population 25–64). Explanatory variable (fborn): Share of migrants 25–64 (% of the total population 25–64). Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The “adjusted” share of natives in each type of job (telework, essential, income-safe) in a given NUTS2 region and year is the share of natives in that type of job minus the expected share of natives in that type jobs in the region given its individual level characteristics (age, education, gender), so the mean is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

due to a greater ability of well-educated native workers to switch occupations, and to stronger complementarities between natives and immigrants at higher skill levels.

The possibility of working from home shields workers from the negative economic outcomes arising from mobility restrictions and lockdowns during the COVID-19 pandemic. As discussed in Section 3, certain occupations are deemed essential by governments. These occupations do not face the same mobility restrictions because they are important for the functioning of the economy and the delivery of critical services such as health care, transportation, and safety. A job that has at least one of these features—either essential or teleworkable—protects the job holder from the supply-side threats, making such occupation “income-safe.” Table 5 reports the results of a similar IV estimation for the different categories of jobs, where the dependent variable is the share of natives employed in income-safe jobs which is our third measure of risk exposure. We include the OLS and the IV results for teleworkable jobs (originally reported in columns 3, 6, and 9 in Table 1) in columns 1–3 for ease of comparison. Interestingly, while there is a strong positive impact of migration on the expansion of telework jobs, the effect is not significant for essential occupations. This is likely to be related to the different nature of these jobs. While telework jobs tend to be concentrated among the highly educated and highly paid information technology and service jobs, a large share of essential jobs is found in low-paid occupations in agriculture, transport, and domestic work. While there are high-skilled occupations such as medical professionals among

the essential jobs, they do not necessarily dominate the list. Thus, we find there is a positive but mostly insignificant impact of immigration on income-safe jobs.

The impact of immigration on the share of native workers in essential jobs does not show much variation across education categories. The impact of immigrants of high or low education levels on natives with the same education levels is not significant in terms of essential jobs (Table A6 in the Appendix). However, we see that highly educated natives tend to move out of essential jobs, in the presence of more immigrants with low levels of education (columns 3 and 4, Table A6 in the Appendix). In terms of combined effects, as it was the case with the previous table, there is no significant impact on movement toward or away from income-safe jobs for natives in either education category.

Another source of exposure to COVID-19 risk that has become salient with the onset of the pandemic is the potential exposure to health risks. These tend to arise from the necessity to have face-to-face interactions with other people as workers perform the duties required by their jobs. As previously mentioned, we define jobs that place one's health at risk as those that are essential (continuing even during the peak of the pandemic) but cannot be performed from home; these jobs instead require frequent in-person contact with customers, suppliers or other colleagues. Around 17% of the jobs in our sample fall into the high health-risk category. As Table 6 shows, the impact of migration on the share of health-safe jobs among natives is positive and highly significant. In other words, migrants encourage and enable natives to move into safer jobs both in terms of income and health exposure. A 1 percentage point increase in the share of immigrants in the labor force leads to an almost 0.5 percentage point increase in the share of health-safe jobs among natives. By education group, this positive impact is again concentrated among tertiary-educated natives in locations where the impact of immigration of workers with low levels of education is especially strong. In contrast, natives with low levels of education experience no significant change in the share of health-safe jobs due to migration.

The previous specifications implicitly assume a contemporaneous effect of immigrants' presence on natives' occupational choices. However, this effect may take time to materialize and occur with a lag as natives respond to an immigrant influx. To investigate this possibility, we follow the approach of Jaeger et al. (2018) by adding the lagged share of immigrants as a regressor and instrumenting it. As shown in Table 7, the coefficient on the contemporaneous immigrant share—our original regressor—remains positive, but the magnitude of the lagged immigrant share is larger and statistically significant in explaining the share of natives in telework jobs. Therefore, it does appear that most of the causal effects of immigrants' presence on natives' employment in teleworkable jobs takes some time to materialize and occurs with a lag.

5.2 | Wage and employment effects of immigration

Results reported in the previous section show strong compositional effects, with native-born workers moving to certain occupations in response to labor supply shocks derived from the unequal composition of migration waves across Western European regions. In this section, we examine whether immigration impacted natives' overall employment levels. Our goal is to shed light on whether the increase in the share of native workers employed in jobs protected from COVID-19 was purely driven by a reallocation from less safe to safer jobs, or also by changes in the *overall* employment levels of native workers. Table 8 reports the OLS and IV estimates for the employment effects of immigration on natives, which also control for year and NUTS2-region fixed effects. The OLS estimates (column 1, Table 8) show a slightly positive impact of migration

TABLE 6 Impact of migration on the share of natives 25–64 in health-safe jobs

Variables	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		
	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	
Total																	
Fborn	0.451*** (0.148)	0.485*** (0.175)	0.624** (0.314)	0.748** (0.361)	1.686** (0.729)	1.714** (0.728)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)	0.030 (0.292)
Constant	-0.111*** (0.042)	-0.121** (0.050)	-0.140 (0.089)	-0.175* (0.102)	-0.444** (0.207)	-0.452** (0.207)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)	-0.004 (0.084)
Observations	982	982	980	980	982	982	982	982	982	982	982	982	982	982	982	982	982
R-squared	0.786	0.778	0.530	0.487	0.598	0.599	0.835	0.835	0.835	0.835	0.835	0.835	0.835	0.835	0.835	0.835	0.835
Dep. var. SD	0.031	0.031	0.036	0.036	0.036	0.036	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
NUTS-2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: “Adjusted” share of natives in health-safe jobs (not essential | not F2F | teleworkable) (% of the total native population 25–64). Explanatory variable (fborn): Share of migrants 25–64 (% of the total population 25–64). Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The “adjusted” share of natives in health-safe jobs in a given NUTS2 region and year is the share of natives in health-safe jobs minus the expected share of natives in health-safe jobs in the region given its individual level characteristics (age, education, gender), so the mean is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.** $p < .05$.*** $p < .01$.

TABLE 7 Impact of migration using current and lagged share of migrants (according to Jaeger et al., 2018)

Variables	(1) 2SLS-MOP telework	(2) 2SLS-PS telework	(3) 2SLS-MOP essential	(4) 2SLS-PS essential	(5) 2SLS-MOP income-safe	(6) 2SLS-PS income-safe	(7) 2SLS-MOP health-safe	(8) 2SLS-PS health-safe
Fborn	0.223 (0.260)	0.252 (0.206)	0.053 (0.418)	-0.096 (0.271)	0.337 (0.376)	0.244 (0.244)	0.261 (0.362)	0.218 (0.248)
fborn $t - 1$	0.537* (0.325)	0.544** (0.278)	-0.567 (0.451)	-0.458* (0.298)	0.233 (0.481)	-0.113 (0.361)	0.285 (0.381)	0.305 (0.273)
Constant	-0.203** (0.084)	-0.213** (0.089)	-0.163** (0.076)	-0.118** (0.047)	-0.008 (0.100)	-0.015 (0.095)	-0.156*** (0.060)	-0.149*** (0.051)
Observations	859	859	859	859	859	859	859	859
R-squared	0.945	0.944	0.861	0.869	0.941	0.944	0.780	0.783
Dep. var. SD	0.054	0.054	0.041	0.041	0.063	0.063	0.031	0.031
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No
NUTS-2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: "Adjusted" share of natives in each type of occupation (% of the total native population 25–64). Explanatory variable (fborn): Share of migrants 25–64 (% of the total population 25–64) and its one-year lag (fborn $t - 1$). Units of observation are the 124 NUTS-2 regions within EU countries, observed yearly from 2011 to 2018. The "adjusted" share of natives in each type of job (telework, essential, income-safe, health-safe) in a given NUTS2 region and year is the share of natives in that type of job minus the expected share of natives in that type jobs in the region given its individual level characteristics (age, education, gender), so the mean is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS-2 in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

TABLE 8 Impact of migration on the share of natives 25–64 in employment

Variables	(1)	(2)	(3)
	OLS	IV-PS	IV-MOP
fborn	0.149** (0.068)	0.087 (0.330)	0.121 (0.357)
Constant	−0.028 (0.019)	−0.011 (0.094)	−0.020 (0.102)
Observations	982	982	982
R-squared	0.939	0.939	0.939
Dep. var. SD	0.084	0.084	0.084
Year FE	Yes	Yes	Yes
Country FE	No	No	No
Nuts2 FE	Yes	Yes	Yes

Note: Dependent variable: “Adjusted” share of natives in employment (% of the total native population 25–64). Explanatory variable (fborn): Share of migrants 25–64 (% of the total population 25–64). Units of observation are the 124 NUTS-2 regions within EU countries, observed yearly from 2011 to 2018. The “adjusted” share of employed natives in a given NUTS2 region and year is the share of employed natives minus the expected share of employed natives in the region given its individual level characteristics (age, education, gender), so the mean is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS2 level in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

on employment rates of natives aged 25–64. However, once the endogeneity issues are addressed, the coefficients for the IV regressions become smaller, and the overall effect becomes statistically insignificant.

We also extend the analysis to different age groups. Similarly, we find again a “close to zero” impact on employment for the prime working age population groups between 25–34 and 35–54 years old (Table A7 in the Appendix). Interestingly, there is a significant reduction in employment rates for the youngest group (between the ages of 15–24). This result is not associated with a significant drop in labor force participation, but rather with higher unemployment rates. In contrast, older working-age natives (ages 55–64) see an increase in their employment rate due to higher immigration rates, indicating that older workers are able to stay in the labor force longer. The overall null effect of migration on employment however masks important gender differences (Table A8 in the Appendix). While there is a nonsignificant reduction in employment rates of male natives (columns 1 and 2), there is an increase in employment rates of females due to the arrival of migrants (columns 3 and 4 of Table A8 in the Appendix). These findings are in line with earlier studies in the US (Cortes & Tessada, 2011), and suggest that migrants—especially those working in personal care, domestic care or household services—can alleviate the pressure on women due to activities (such as housekeeping and caring for children and the elderly) that traditionally keep them detached from the labor market. When we explore the impact across different education groups, we again fail to find any statistically significant effect. Even though the

TABLE 9 Impact of migration on the share of natives in top 3 deciles of income by type of occupation

Variables	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)	
	Total employees		Telework employees		Essential employees		Income-safe employees		Health-safe employees											
	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP
fborn	-0.075 (0.330)	-0.085 (0.378)	-0.770 (0.478)	-0.880 (0.552)	-0.168 (0.429)	-0.322 (0.487)	-0.208 (0.362)	-0.314 (0.413)	-0.068 (0.495)	-0.025 (0.570)										
Constant	0.036 (0.091)	0.039 (0.105)	0.308** (0.132)	0.366** (0.153)	0.071 (0.119)	0.114 (0.135)	0.117 (0.100)	0.146 (0.114)	0.039 (0.136)	0.028 (0.157)										
Observations	781	781	781	781	781	781	781	781	781	781										
R-squared	0.898	0.898	0.803	0.787	0.830	0.826	0.879	0.876	0.770	0.771										
Dep. var. SD	0.064	0.064	0.073	0.073	0.069	0.069	0.067	0.067	0.070	0.070										
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes										
Country FE	No	No	No	No	No	No	No	No	No	No										
NUTS-2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes										

Note: Dependent variable: "Adjusted" share of natives in the top 3 deciles of income (% of the total native population 25–64). Explanatory variable (fborn): Share of migrants 25–64 (% of the total population 25–64). Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The "adjusted" share of natives in the top 3 deciles of income in a given NUTS2 region and year is the share of natives in the top 3 deciles minus the expected share of natives in the top 3 deciles in the region given its individual level characteristics (age, education, gender), so the mean is close to zero. Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach according to Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach according to Mitaritonna et al. (2017). Dep. var. SD = Standard deviation of the dependent variable. Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.
 ** $p < .05$.
 *** $p < .01$.

employment effect is positive for the highly educated and negative for those with lower levels of education, the effects are not precisely estimated.

Finally, we examine the impact of immigration on natives' wages, the focus of many papers in the literature (see World Bank, 2018 for a review). Results in Table 9 show that we again fail to find any significant impact of migration on natives' wages. As a caveat to these findings, we underscore that the EU Labour Force Survey only provides information on the wage decile of workers in a given country, not their actual wages. In order to circumvent this problem, we construct a variable that measures the gap between the actual and expected probability of being in the top three income deciles given individual-level characteristics (age, gender, education levels), and that varies by NUTS2 region and year. The impact of migrants' presence on the wage-gap variable, however, remains not statistically different from zero, a result that holds when looking at the share of top three wage deciles of teleworkable, essential, income-safe and health-safe jobs. These results are robust to alternative versions of the dependent variable, such as the share of employees in the bottom three deciles, or the income decile estimated using ordered probit regressions in the initial stage. Therefore, the adjustment in the labor market after the arrival of migrants seems to happen through the composition of employment but does not affect the relative or absolute wages of the different types of occupations in line with a more competitive and mobile labor market.

6 | CONCLUSION

This article provides evidence that exposure to negative economic shocks and health risks associated with the COVID-19 pandemic is greater among immigrant workers than among native-born people in high-income Western European countries. Using data from the European Union Labour Force Survey for 2011–2018, we show that this greater risk exposure stems from systematic differences in occupations of immigrant and native workers. Immigrant workers have significantly lower presence in occupations that can be performed from home (telework), and higher presence in occupations listed as “essential.” Moreover, immigrants are more likely to be employed in jobs that combine both features—taking on work that is deemed to be essential *and* requires face-to-face contact. Thus, immigrant workers are more likely to bear a greater brunt of the economic and health risks of the pandemic than native-born workers.

The arrival of immigrants to a regional labor market in the EU, in itself, had a causal impact on the occupational shift of natives, contributing to lower levels of exposure to the pandemic related risks. Our results show that native-born workers—especially those with tertiary education living in regions with a higher share of migrant workers—are more often employed in occupations that can be carried out from home, which we refer to as the ability to telework. These effects are large in magnitude and hold when Bartik-type instruments are used to account for the endogeneity of immigrants' locations and occupation choices. However, the positive impact of immigration—is concentrated among native workers with high levels of education. Those native workers with less schooling, in contrast, do not seem to be affected much from immigration.

In addition to the ability to telework, we explore several other occupational characteristics in relation to COVID-19 related risks. The first one is whether an occupation is considered essential. Based on governmental regulations, essential jobs cover a wide skill range from low skilled ones (in certain retail sectors) to high-skilled ones in medical professions. Next, we classify certain jobs as income-safe if they are either essential or could be performed via telework. Our results

show that the presence of immigrants in a certain subregion does not have a significant effect on the share of native workers employed in essential or income safe jobs. This is different from the case of teleworkable jobs and it is likely to be due to the high share of low-skilled jobs in essential occupations (such as retail and transportation) that attract large numbers of migrants. However, these low-skilled essential jobs tend to entail larger health risks as they often require physical interactions with other people. Based on our last measure of job exposure to health-risks we also find that the presence of immigrants causes native workers to move towards occupations that are less exposed to health risks. These effects are again stronger for the highly educated natives.

We finally analyze the potential impact of immigration on changes in the overall employment levels and wages of native workers as it impacts occupational composition. In contrast with the large occupational shifts, we find no absolute employment or wage effects in the EU. These results are consistent across education levels.

In many countries, many migrants perform the dirty, dangerous and demeaning jobs—sometimes referred to as “3D jobs”—that natives are unwilling to do. The evidence from the COVID-19 pandemic is pointing in the same direction. As more evidence emerges, especially on labor market outcomes during the pandemic, we expect the immigration policies of the post-COVID era will be shaped accordingly.

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DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available from EUROSTAT. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from EUROSTAT: <https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey>.

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ENDNOTES

- ¹ Prominent examples in the literature include studies of network effects (Beaman, 2012; Munshi, 2003), educational downgrading (Chiswick et al., 2005; Dustmann et al., 2013), limited language skills (Borjas, 2015; Friedberg, 2000), and barriers to recognition of foreign occupational qualifications (Brücker et al., 2021).
- ² We perform the empirical analysis at the NUTS2 (Nomenclature of Territorial Units for Statistics) level. This is a geocode standard adopted by the EU to reference subdivisions of countries for statistical purposes. Each NUTS region includes between 800 thousand and 3 million people and is based on administrative boundaries of countries. Some smaller countries (such as Cyprus, Estonia, or Malta) have 1 NUTS2 region while larger countries have a larger number of subregions (such as 39 in Germany and 27 in France). Our dataset has 124 regions in total.
- ³ As noted by Fasani and Mazza (2020b), while the economic vulnerability measures such as essentiality, temporariness, teleworkability, and industry resilience strongly predict employment outcomes after COVID-19, these

- characteristics did not have any predictive power prior to the pandemic. In addition, COVID-exposed occupations had a negative wage premium, contrary to the expected compensating wage differential that one would expect if workers in these occupations had realized such increased risks (Basso et al., 2020).
- ⁴ EU15 comprises the higher-income EU countries that were members before accession of the 10 new members in 2004. These are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom.
- ⁵ The New Member States (NMS13) and their accession dates are the following: Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovak Republic, Slovenia (2004); Romania, Bulgaria (2007); Croatia (2013).
- ⁶ These high-income OECD members are Australia, Canada, Japan, New Zealand, and the United States.
- ⁷ The scheme changed from ISCO-88 to ISCO-08.
- ⁸ The dataset does not include information on the exact wage of individuals.
- ⁹ [https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020XC0330\(03\)](https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020XC0330(03))
- ¹⁰ This result is slightly higher than Fasani and Mazza (2020a) who estimate that 33% of workers in the EU work in essential sectors. The disparities emerge as we include the occupations related to “Agriculture, Forestry and Fishery Laborers” (ISCO-08 code 921), as well as an approximation of essential occupations at the 2-digit level for Bulgaria, Poland, and Slovenia as the EU-LFS does not include 3-digit occupations for those countries.
- ¹¹ Jobs with high face-to-face interactions involve tasks such as establishing and maintaining personal relationships, assisting and caring for others, performing for or working directly with the public, or selling to or influencing others through extensive personal interaction (Garrote-Sanchez et al., 2020).
- ¹² The correlation is 0.45 but still statistically significant at the 1% level.
- ¹³ This correlation coefficient is 0.31 and again significant at the 1% level.
- ¹⁴ For prior studies using Bartik-type instruments to study the impact of migration shocks, see Jaeger (2006), Edo et al. (2019), Mitaritonna et al. (2017), and Peri and Sparber (2009). Jaeger et al. (2018) provide a detailed review of this literature and offer potential caveats about the validity of this instrument.
- ¹⁵ The earliest year for which information on workers’ country of origin is available in the EU-LFS is 2002. Our instrument, however, does not distinguish the lagged immigrant shares by migrants’ region of origin as some destination countries in the EU-LFS do not provide the region of origin breakdown.
- ¹⁶ A large body of literature documents the role played by migrants’ networks and diasporas in affecting the location choices of new migrants. See, for example, Munshi and Rosenzweig (2006), Beine et al. (2011), Beaman (2012), Patel and Vella (2013), and Kramarz and Skans (2014), among others.
- ¹⁷ In Section 5, we evidence that the first stage of the IV estimation is weaker than what has been evidenced in the US context, once region fixed effects are accounted for.
- ¹⁸ Results with these alternative instruments are available upon request.

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APPENDIX A

TABLE A1 Descriptive statistics of the EU15+EFTA population in 2018

	All population 25–64				Males 25–64		Females 25–64	
	Size (% total)	% males	Mean age	% tertiary education	Mean age	% tertiary education	Mean age	% tertiary education
Native-born	81.3	50.2	45.4	33.5	45.2	32.8	45.6	34.3
Migrants	18.7	48.4	43.0	31.2	43.0	30.0	43.0	32.3
Migrants from EU15+EFTA	3.1	51.8	45.3	43.0	45.1	41.9	45.4	44.2
Migrants from NMS13	3.6	46.1	41.9	27.3	41.7	23.7	42.0	30.3
Migrants from non-EU Europe	3.5	47.6	43.5	21.2	43.6	18.0	43.5	24.0
Migrants from rest of world	8.1	48.5	42.5	31.4	42.4	31.4	42.5	31.3

Source: Own elaboration based on the EU-Labor Force Survey.

TABLE A2 Labor market statistics of the EU15 population (25–64) in 2018

	Total			High education		Low education	
	Total	Natives	Migrants	Natives	Migrants	Natives	Migrants
Population (1000)	270,026	219,628	50,398	73,571	15,602	145,775	34,440
Share	100.0	81.3	18.7	82.5	17.5	80.9	19.1
Unemployment rate	6.1	5.4	9.0	3.4	6.6	6.6	10.2
Employment rate	76.3	77.6	70.7	87.5	79.2	72.6	67.0
% telework jobs	38.4	40.9	27.3	62.1	52.1	28.0	14.1
% essential jobs	38.4	37.6	41.8	43.4	44.5	34.1	40.4
% income-safe jobs	64.2	65.3	59.3	81.4	75.6	55.6	50.6
% health-safe jobs	83.1	84.4	77.1	88.2	83.1	82.1	73.9

Source: Own elaboration based on the EU-Labor Force Survey.

TABLE A3 Share of workers in the top 3 deciles of wages in 2018

	Total			High education		Low education	
	Total	Natives	Migrants	Natives	Migrants	Natives	Migrants
Total employees	33.0	35.0	24.4	57.4	47.1	23.1	15.0
Telework employees	47.7	47.9	46.8	62.0	59.0	30.9	25.5
Essential employees	34.6	37.2	23.2	59.5	50.7	22.1	10.9
Income-safe employees	38.2	40.3	28.7	60.2	53.0	24.9	13.5
Health-safe employees	35.6	37.3	28.1	58.5	49.5	24.8	17.7

Source: Own elaboration based on the EU-Labor Force Survey.

TABLE A4 Labor market statistics of the EU15 population (25–64) in 2018 by gender

	Total				High education				Low education			
	Natives		Migrants		Natives		Migrants		Natives		Migrants	
	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females
Population (1000)	110,159	109,469	24,418	25,980	36,083	37,487	7267	8335	73,928	71,848	16,956	17,484
Share	81.9	80.8	18.1	19.2	83.2	81.8	16.8	18.2	81.3	80.4	18.7	19.6
Unemployment rate	5.2	5.5	8.3	9.8	3.0	3.7	5.7	7.6	6.4	6.7	9.6	11.1
Employment rate	82.3	72.8	79.9	62.1	90.2	84.8	86.5	72.8	78.5	66.6	77.1	57.2
% telework jobs	36.4	45.9	24.9	30.2	61.2	63.1	52.7	51.5	22.6	34.5	11.7	17.3
% essential jobs	37.7	37.6	36.9	47.8	44.4	42.4	45.4	43.7	33.9	34.4	32.8	50.4
% income-safe jobs	61.0	70.2	51.6	68.6	81.0	81.7	74.1	77.1	49.8	62.6	40.7	63.4
% health-safe jobs	88.6	79.7	85.7	66.7	92.2	84.1	88.0	78.0	86.6	76.8	84.7	59.8

Source: Own elaboration based on the EU-Labor Force Survey.

TABLE A5 Share of workers in the top 3 deciles of wages in 2018 by gender

	Total						High education						Low education					
	Natives			Migrants			Natives			Migrants			Natives			Migrants		
	Males	Females		Males	Females		Males	Females		Males	Females		Males	Females		Males	Females	
Total employees	47.0	22.4		32.6	14.8		34.3	42.9		22.5	34.6		34.3	11.2		22.5	5.6	
Telework employees	66.6	33.0		61.9	32.6		77.0	47.8		73.1	44.3		51.0	17.8		39.1	14.9	
Essential employees	50.1	23.3		35.2	12.3		72.1	45.6		63.4	35.6		34.9	8.4		19.9	3.6	
Income-safe employees	55.8	26.6		41.1	18.0		74.6	46.0		66.5	39.3		39.7	12.9		22.9	6.2	
Health-safe employees	48.4	24.6		34.1	18.9		72.4	43.7		61.0	36.4		35.0	12.6		23.3	7.5	

Source: Own elaboration based on the EU-Labor Force Survey.

TABLE A6 Impact of migration on the share of natives 25–64 in essential and income-safe jobs by education levels

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Essential jobs						Income-safe jobs					
	High-educ mig on high-educ natives	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	High-educ mig on high-educ natives	IV-PS	IV-MOP	High-educ mig on high-educ natives	IV-PS	IV-MOP
fborn	-0.409 (0.319)	-0.337 (0.363)	-1.144** (0.518)	-1.069* (0.549)	-0.246 (0.328)	-0.177 (0.298)	0.745 (0.475)	0.922* (0.539)	0.278 (0.492)	0.338 (0.466)	-0.043 (0.436)	-0.103 (0.424)
Constant	0.115 (0.090)	0.094 (0.103)	0.325** (0.148)	0.304* (0.157)	0.081 (0.094)	0.061 (0.085)	-0.189 (0.136)	-0.240 (0.155)	-0.058 (0.141)	-0.075 (0.133)	0.045 (0.125)	0.061 (0.121)
Observations	980	980	982	982	982	982	980	980	982	982	982	982
R-squared	0.860	0.864	0.775	0.786	0.852	0.860	0.909	0.899	0.927	0.926	0.910	0.908
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No	No	No	No	No
Nuts2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: “Adjusted” share of high-educated or low-educated natives 25–64 in essential or income-safe jobs. Explanatory variable (fborn): Share of high-educated (hs) or low-educated (ls) migrants (% of the high-educated or low-educated population 25–64). Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The “adjusted” share of natives in essential/income-safe jobs in a given NUTS2 region and year is the share of natives in essential/income-safe jobs minus the expected share of natives in essential/income-safe jobs in the region given its individual level characteristics (age, education, gender). Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach as in Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach as in Mitritonna et al. (2017). Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.** $p < .05$.*** $p < .01$.

TABLE A7 Impact of migration on the share of natives in employment by age group

Variables	(1) Age 15–24		(2)		(3) Age 25–34		(4)		(5) Age 35–54		(6)		(7) Age 55–64		(8)		
	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	
fborn	−0.753** (0.341)	−0.802** (0.337)	0.104 (0.480)	0.095 (0.497)	−0.279 (0.514)	−0.347 (0.544)	0.128 (0.147)	0.147 (0.155)	−0.343** (0.139)	−0.347 (0.155)	0.940* (0.488)	−0.347 (0.544)	0.940* (0.488)	−0.343** (0.139)	0.940* (0.488)	−0.343** (0.139)	1.074** (0.454)
Constant	0.276*** (0.097)	0.290*** (0.096)	0.221 (0.141)	0.193 (0.141)	0.128 (0.147)	0.147 (0.155)	0.128 (0.147)	0.147 (0.155)	−0.343** (0.139)	−0.343** (0.139)	−0.343** (0.139)	−0.343** (0.139)	−0.343** (0.139)	−0.343** (0.139)	−0.343** (0.139)	−0.343** (0.139)	−0.382*** (0.129)
Observations	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982	982
R-squared	0.930	0.927	0.835	0.838	0.895	0.893	0.895	0.893	0.895	0.895	0.898	0.893	0.895	0.898	0.898	0.891	0.891
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
NUTS-2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: “Adjusted” share of natives (either 25–34 or 35–54) in employment. Explanatory variable (fborn): Share of migrants over the total working-age population. Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The “adjusted” share of employed natives in a given NUTS2 region and year is the share of employed natives minus the expected share of employed natives in the region given its individual level characteristics (age, education, gender). Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach as in Pelt and Sparber (2009). IV-MOP stands for the instrumental variable approach as in Mitaritonna et al. (2017). Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

TABLE A8 Impact of migration on the share of natives in employment by gender and education

Variables	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)	
	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP	IV-PS	IV-MOP
fborn	-0.343 (0.459)	-0.296 (0.480)	0.568* (0.318)	0.600* (0.339)	0.579 (0.501)	0.738 (0.541)	-0.158 (0.465)	-0.009 (0.468)	-0.455 (0.670)	-0.448 (0.613)										
Constant	0.073 (0.131)	0.060 (0.137)	-0.107 (0.091)	-0.116 (0.097)	-0.125 (0.143)	-0.170 (0.155)	0.084 (0.133)	0.041 (0.134)	0.132 (0.191)	0.130 (0.175)										
Observations	982	982	982	982	980	980	982	982	982	982										
R-squared	0.854	0.856	0.944	0.943	0.904	0.898	0.911	0.913	0.900	0.908										
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes										
Country FE	No	No	No	No	No	No	No	No	No	No										
NUTS-2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes										

Note: Dependent variable: "Adjusted" share of natives 25–64 in employment (males, females, high-educated and low-educated). Explanatory variable (fborn): Share of migrants over the total working-age population. Units of observation are the 124 NUTS-2 regions within Western European countries, observed yearly from 2011 to 2018. The "adjusted" share of employed natives in a given NUTS2 region and year is the share of employed natives minus the expected share of employed natives in the region given its individual level characteristics (age, education, gender). Time-variant NUTS-2 observations are pooled to run the regressions. IV-PS stands for the instrumental variable approach as in Peri and Sparber (2009). IV-MOP stands for the instrumental variable approach as in Mitaritonna et al. (2017). Clustered standard errors at the NUTS-2 level in parentheses.

* $p < .1$.** $p < .05$.*** $p < .01$.