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**“IMMIGRATION AND NATIVES’ TASK SPECIALIZATION:
EVIDENCE FROM ITALY”**

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Firma dello studente

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Abstract

Empirical studies about the impact of immigration on the main labor market outcomes of the host country have not found unambiguously evidence of the detrimental effect predicted by the theory. A possible explanation could be the fact that natives are able to elude the increasing immigrants-induced competition by specializing in those jobs in which they have a comparative advantage on immigrants. Using occupational task-intensity data from the O*NET dataset and Italian Labor Force Survey data from 2014 to 2019, I demonstrate that, because of immigration, natives reallocate their task supply towards more communicative-intensive jobs and leave those manual-intensive. In particular, I find that a 1% increase in the share of immigrants is associated with a 0.72% rise in the relative supply of communicative versus manual tasks.

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Chapter 1

Introduction

Migration is surely a long-standing phenomenon in human history. In more recent years, however, migration has assumed a series of characteristics that have dramatically changed its importance among policymakers' priorities.

Firstly, globalization and technological progress have been able to reduce the “distances” between the different parts of the world, facilitating the movement of people and consequently increasing the magnitude of the international flows. United Nations estimates that in the last 20 years the number of people living in a country which is not that where they were born has almost doubled, passing from 150 to 272 million globally. Moreover, it is worth noting that the growth rate of migrants is even higher than that of the world population itself, the reason why the share of foreign-born individuals over the total population increased from 2.8% in 2000 to 3.5% in 2020 (United Nations, 2020). And this trend is expected to remain the same for many years, as the population in the main sending countries is projected to continue to increase at a very high pace.

Secondly, the patterns through which immigration happens are completely changed compared to the first half of the previous century. In fact, the number of migrants not only increased in traditional receiving countries such as the United States, but also in other developed countries with little experience of labor force import and even in historical immigrants-sending countries, like Spain or Italy. Including the fact that two-thirds of the total migrants decide to emigrate for working reason is considered, it is clear that immigrants have inevitably become a structural part of the labor force in an increasing number of developed countries.

Lastly, the concomitance of this large increase in the number of people emigrating from their country of origin with a deep economic crisis like that occurred in 2008 also created an intense climate of aversion towards immigrants from the majority of the public opinion. This widespread sentiment actually has given rise to the ascension of many populist and anti-

immigration parties in almost all developed countries, the most representative examples given by the election of Donald Trump as U.S. President in 2016 and his propose of building “the Wall” on the U.S. Mexican borders and the victory of the “Leave” in the “Brexit” referendum in the same year, with the consequential decision of the United Kingdom of leaving the European free labor market.

For all these reasons, immigration has recently attracted increasing attention also in the academic environment. The new challenges and questions arose from the great inflow of people in an always larger number of receiving countries have led many economists to spend more time and effort addressing this topic, especially for its policy implications. This has obviously resulted in a vast literature concerning the relationship between this demographic phenomenon and different aspects of the society: to make just some examples, economists have studied how immigration affects innovation (Hunt and Gauthier-Loiselle, 2010; Ozgen et al., 2012), fiscal balances (Lee and Miller, 2000), but also crimes (Bell et al., 2013) and voting (Halla et al., 2017). However, the topic on which scholars have focused the most is indeed the effect on labor market outcomes. Economists have investigated for decades how the arrival of people from foreign countries may affect wages and employment opportunities of natives, both from a theoretical and an empirical point of view. However, while the canonic theoretical models have reached unambiguously negative conclusions (even though extremely sensitive to the assumptions imposed), the multitude of empirical studies on the impact of immigration in the host country labor market has not been able to confirm unequivocally such results.

These outcomes prompt some researches to extend the theoretical models, taking into account the possibility that labor markets may actually be able to fully absorb immigration without experiencing any negative impact. In this regard, an example is provided by Lewis (2013), who shows that allowing firms to change their technology in production after immigration could significantly lower the negative effects induced by the introduction of the foreign-born workers in the labor market. This dissertation, however, tries to find evidence supporting the intuition developed by Peri and Sparber (2009): their idea is that natives and immigrants cannot be considered as perfect substitutes since the former have inevitably a better knowledge of the language (at least among low-skilled workers). Under this assumption, an increase in the share of immigrants increases the supply of manual-intensive jobs (in which immigrants have a comparative advantage), lowering the wage of these occupations. The fundamental difference, however is that in this context natives do not suffer passively this drop in compensation but react by specializing in those jobs in which immigrants cannot compete, that is those in which communication and language proficiency are relatively more important.

To prove this, I use Italian Labor Force Survey data from 2014 to 2019. Following the example of Peri and Sparber (2009), I match each individual's occupation in my database with an index measuring the relative supply of communicative versus manual tasks related to that job. In particular, in order to compute this indicator I exploit the O*NET database provided by the U.S. Department of Labor, which furnishes information about the importance of 52 distinct employee abilities for more than 950 occupations. Subsequently, I consider each Italian provinces as an independent local labor market and, using a spatial approach, I estimate the effect that an increase in the share of immigrants has on the relative communicative task supply of a native individual. This kind of approach, however, suffers from an endogeneity problem, since immigrants are not randomly distributed among local labor markets. For this reason, I rely on an Instrumental Variable approach, by using immigrants distribution by country of origin in 2003 as a proxy for the share of foreign-born workers in a local labor market. The results confirm the theoretical assumptions, finding that a one percentage-point rise in the share of immigrants in a local labor market is associated with a 0.72 percent increase in the relative supply of communicative versus manual tasks by natives. In particular, this increase is mostly explained by a drop in the supply of manual tasks, rather than by an increase in the supply of communicative ones.

This thesis is so structured: Chapter 2 initially summarizes the main predictions of different theoretical models concerning the labor market effects of immigration (including the theoretical model of Peri and Sparber 2009 about natives' task specialization) and later, briefly review the vast empirical literature on the topic; Chapter 3, after having reported some telling data about immigration in Italy during my period of analysis, describes my database and explains the empirical strategy that I have chosen to employ in order to correctly estimate my causal effect of interest, focusing especially on the construction and the validity of the shift-share instrument I used; Chapter 4 reports the main results of my analysis, performing also some robustness checks and the Oster test for eventual omitted variable bias; Chapter 5 concludes.

Chapter 2

The Labor Market Effects of Immigration

In this chapter, I summarize the literature concerning the labor market effects of immigration to analyze what economists already know and also to understand why a recent branch of this literature has focused on the possibility that natives do not suffer in a passive way the new competition arising from immigration but may react to it by changing their role in production. The chapter is so structured: Section 1 explains the theoretical predictions about the impact of immigration, starting from a very simple demand and supply model and then improving it by making more rational assumptions. Afterwards, I show how, by making realistic suppositions on the different abilities of immigrants and natives, the theory is able to predict tasks specialization of natives in response to an immigration shock. In Section 2, instead, I summarize the multitude of empirical works on this topic: initially talking about the labor market impact of immigration in general, showing that even using different techniques, results continue to be conflicting; finally going into the details of those papers more connected with the purpose of this dissertation, and in particular, focusing on the literature concerning task specialization and my country of interest, Italy.

2.1 Theoretical Predictions

2.1.1 Homogeneous Labor

My analysis concerning the effect of immigration on wages and employment of natives starts from a simple model where all workers are considered equal to each other. Although unrealistic, this model is quite useful to understand what are the main forces that an inflow of workers from abroad activates in a labor market.

Suppose for simplicity that the host country economy produces a single good using a production function which combines capital (K) and homogeneous labor (L), so that the output is

equal to $Y = F(K, L)$. This production function is twice differentiable, continuous and concave, so that F_K and $F_L > 0$ and F_{KK} and $F_{LL} < 0$. Moreover, the production function is homogeneous of degree 1, which implies $F_{KL} > 0$. Since labor is homogeneous all workers are perfect substitutes and then the workforce is equal to the sum of natives and immigrants ($L = N + M$).

Let the price of output be fixed and equal to p . I assume the labor market to be fully competitive, which implies that each input price is equal to its value of the marginal product. Therefore, in a pre-immigration equilibrium (where $M = 0$), the price of labor and the rental rate of capital are respectively:

$$w_0 = pF_L(K, N) \quad (2.1)$$

$$r_0 = pF_K(K, N) \quad (2.2)$$

The labor demand function of firms coincides with Equation (2.1), whereas the labor supply of households positively depends on the wage w and is described by a simple linear function $S(w)$.

In the short-run, capital is assumed to be fixed and owned only by natives, so that immigrants do not affect the amount of K . In this simple model, an inflow of immigrants in the country increases the labor force by the same amount, which implies a rightward shift of the labor supply curve. As can be seen from Figure 2.1 and Figure 2.2, the rise in the workforce reduces the amount of physical capital per worker, lowering the marginal labor productivity and, consequently, the market-clearing wage. This is the first result of the model:

Prediction 1 *In a model with homogeneous labor, immigration has the effect of lowering the market wage in the short run.*

Figure 2.1 depicts the effect of immigration when labor supply is finite elastic. From the graph it is possible to see that the supply shock induced by immigration has the effect of increasing the number of employed workers in the economy too; however, it is evident that, in this case, the increase in the aggregate supply of labor is lower than the number of immigrants entering in the market. In fact, while at the old wage w_0 N_0 native workers were employed, now at the new wage w_1 only an amount N_1 of natives is willing to participate in the labor market. It is noteworthy to specify that this reduction in the number of employed natives does not imply an increase in unemployment, but rather in the number of inactive workers.

But this result is heavily conditioned by the assumption I made about the elasticity of labor supply. As can be seen from Figure 2.2, if I assume, instead, that labor supplies of both natives and immigrants are perfectly inelastic, the adjustment process occurring in the labor market after an immigration shock is now fully accommodated through a reduction of the market wage,

Figure 2.1: The effects of immigration with finite elastic labor supply

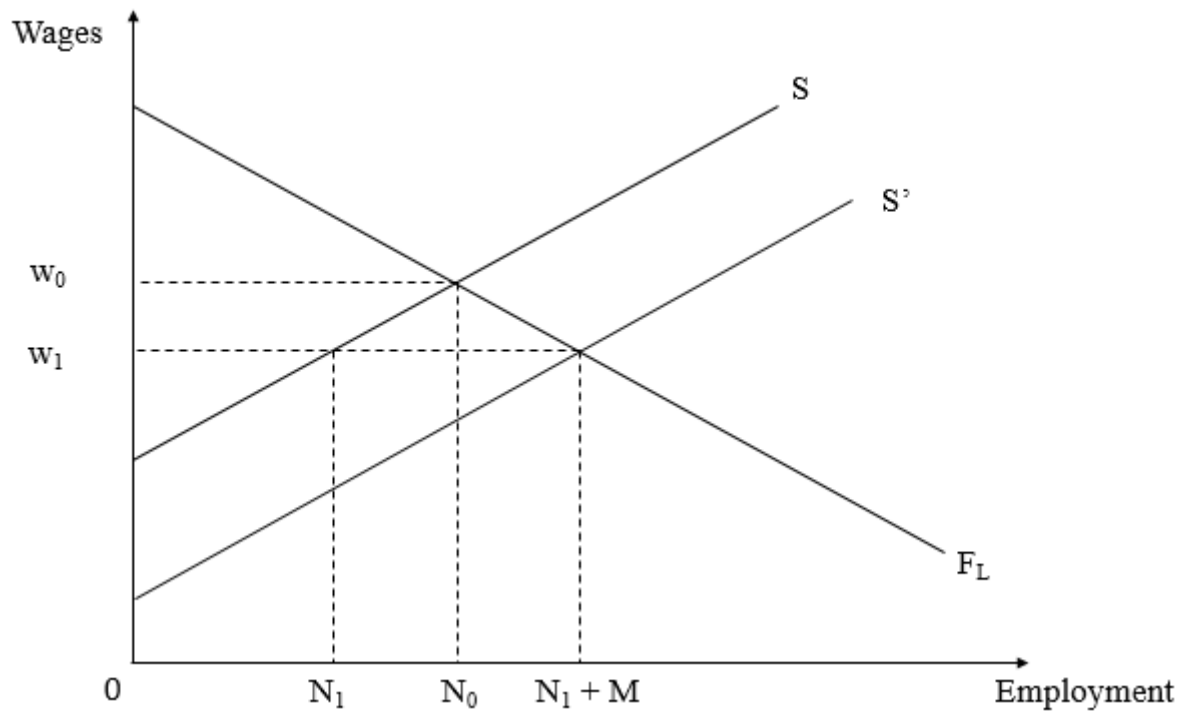


Figure 2.2: The effects of immigration with inelastic labor supply

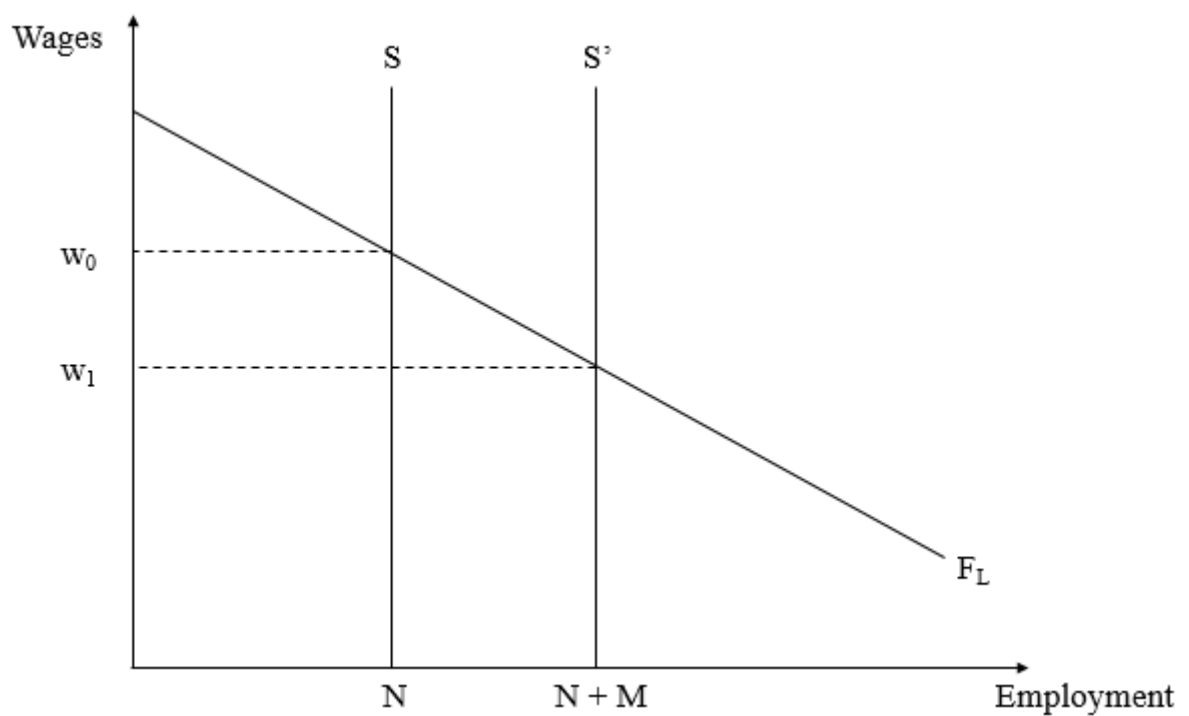
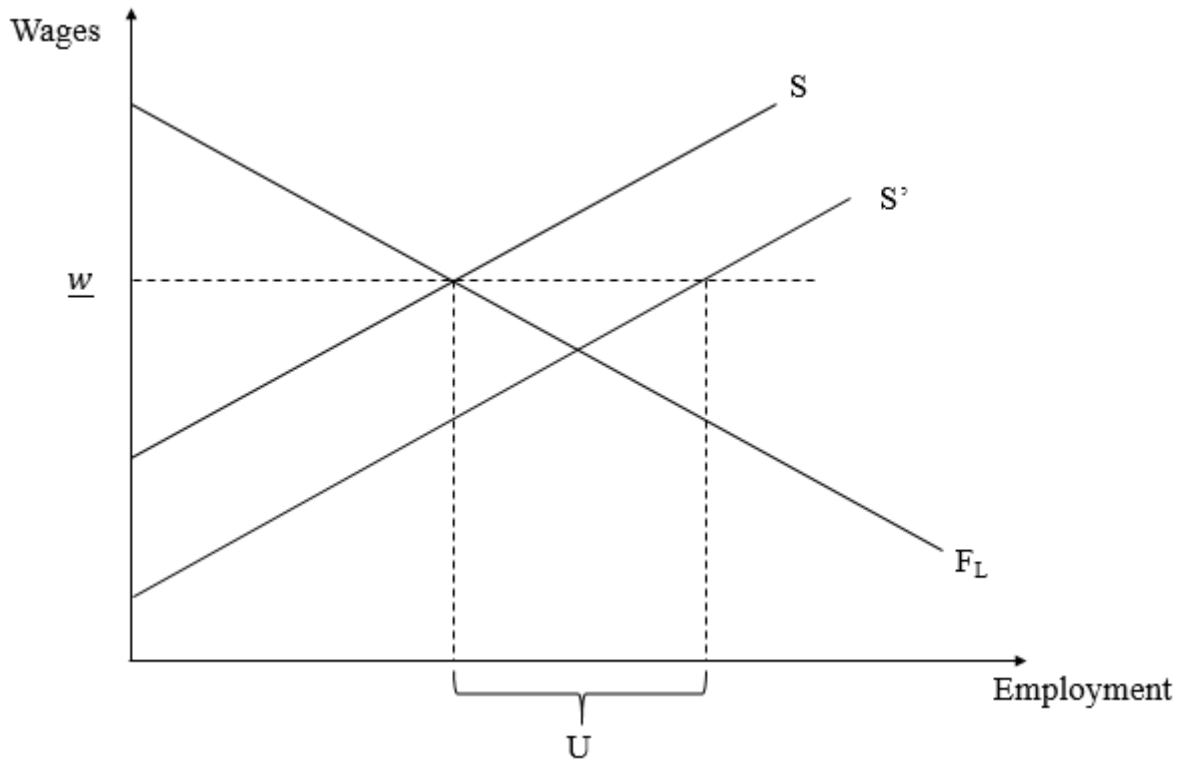


Figure 2.3: The effect of immigration in a market with wage rigidities



triggering no effect on the level of employment among natives.

Prediction 2 *The decrease in wages imposed by immigration reduces the number of natives participating in the labor market, lowering employment among them. This effect is lower the lower the elasticity of labor supply, with no reduction in employment when supply is perfectly inelastic.*

Analyzing European labor markets, it is also important to remember that many countries (including Italy) are characterized by the presence of many institutions (e.g. high minimum wages, strict employment protections and generous unemployment benefits) that, through their effects on the workers' reservation wage and the possibility for firms of firing and hiring their employees, make the wage adjustment process very downwardly rigid. Figure 2.3 shows the effect of immigration in a market where the wage cannot go below its pre-immigration market-clearing level. Obviously, since wage does not decrease, the number of native workers willing to participate in the market remains equal and the post-immigration labor force in the economy is then $N+M$. However, at \underline{w} , firms are willing to hire just N_0 workers, so that M workers become now involuntarily unemployed (Boeri and Van Ours, 2013). The amount of job losses imputable to native workers is difficult to establish *a priori* and depends on the market penetration of immigrants.

Prediction 3 *In a labor market with wage rigidities, immigration increases involuntary unemployment.*

Going back to the generic case with fully flexible wages, the complementarity between the two factor inputs implies that a reduction in the price of labor (which is triggered by immigration) is accompanied by a simultaneous increase in the return of capital¹. In the long run, capital is not fixed anymore and is allowed to adjust to the increased number of workers. The short-run rise in its price encourages inflows of the input until the rental rate in the economy reaches the world price level. At this point, the pre-immigration capital-labor ratio is restored and so it is the marginal labor productivity. In fact, as shown by Borjas (2013), in the long run what he calls the “wage elasticity of immigration” is given by:

$$\left. \frac{d \ln w}{d \ln L} \right|_{dr=0} = s_K c_{LK} + s_L c_{LL} = 0 \quad (2.3)$$

where s_i is the income share accruing to factor i and the last equality follows from the fact that linear homogeneity of the production function implies $\sum_j s_j c_{ij} = 0$. Graphically, this situation is represented by a horizontal labor demand curve at w_0 .

Prediction 4 *In a model with homogeneous labor, in the long run the market wage returns at its pre-immigration level and immigration has the only effect of increasing the scale of the economy.*

In summary, while in the short run immigration should produce negative effects on either natives’ wage or employment or even both simultaneously, in the long run the economy is expected to absorb completely the supply shock without suffering any detrimental consequence.

2.1.2 Heterogeneous Labor

Although the previous model is able to predict well the main effects that an inflow of new workers from abroad has on the labor market, the assumption that all workers are equal (and then hit by immigration in the same way) seems not too realistic. In fact, immigrants are usually concentrated at the opposite extremes of the skill spectrum: as a consequence, immigration not only increases the aggregate number of workers in the economy, but also modify the skill composition of the workforce. In the literature concerning this kind of problem, skills of workers

¹Borjas (2013) shows that $\left. \frac{d \ln r}{d \ln L} \right|_{dK=0} = s_L c_{KL} > 0$ where $c_{KL} = \frac{F_{KL} F}{F_K F_L}$ is defined as the elasticity of complementarity between K and L, which is positive since $F_{KL} > 0$ by linear homogeneity of the production function, and s_L is the income share accruing to labor.

are usually differentiated by their level of educational attainment and their working experience, measured as the number of years passed since they left education.

Models that try to capture the effects of this variation usually rely on a production function of the following type:

$$Y = F(K, L_S, L_U) \quad (2.4)$$

where L_S and L_U are the number of skilled and unskilled workers in the economy, respectively. I assume also that, within each skill group, immigrants and natives are perfect substitutes and that the production function has the same properties as in the homogeneous labor case.

At the aggregate level, the increase in the amount of workforce due to immigration is expected to lower, in the short run, the average wage among skill groups, through a mechanism like that illustrated in the homogeneous labor market². However, in this model this is not the only effect worth of attention:

Prediction 5 *In a model with heterogeneous labor, immigration decreases the relative wage of the group that experiences the larger supply shock (Borjas, 2013).*

Regarding that, suppose, for example, that the economy receives an inflow of immigrants relatively less skilled than natives, which is the case more likely to happen in my country of interest, Italy. Following *Prediction 5*, this inflow will decrease the factor price of unskilled labor with respect to that of skilled one. In fact, it easy to show that the wage of unskilled workers will indeed decline because of the drop in its marginal factor productivity and, though the impact on the wage of the skilled workers is *a priori* ambiguous (the sign depends on the magnitude of the elasticity of complementarity between skilled and unskilled), reasonable simulations show that skilled workers suffer a decline in wage too, but in a smaller proportion than is the case of the unskilled (Cahuc et al., 2014, p. 724). On the contrary, if the inflow of immigrants has the same skill distribution of the native workforce, the relative wage structure will not be affected and the only effect that is expected is that on the mean wage.

In the previous model, I have shown how the effects of immigration can dramatically change by considering the long run rather than the short run. As before, the reduction in the average wage level increases the price of the complementary input, attracting new capitals and restoring the pre-immigration capital-labor ratio. Again this means that, in the long run, immigration leaves the average wage among skill groups unaffected. Moreover, Borjas (2014, p. 69) shows

²In particular, Borjas (2014) shows that in the case of a nested CES production function the decrease in the average wage in the heterogeneous labor model is the same as in the case of homogeneous labor.

that this result is independent of the skill distribution of immigrants. Unlike the mean wage, however, the wage structure of the economy may remain altered even in the long run:

Prediction 6 *In the long run, immigration lowers the wage of the group in which immigrants are relatively more abundant than natives and rises the wage of the group in which natives are relatively more abundant. If immigrants and natives have the same skill distribution there is no effect on the economy wage structure (Borjas, 1999).*

Therefore, in a heterogeneous labor market, the skill distribution of immigrants decides which group of workers gains and which loses from immigration.

2.1.3 The Effects on Task Specialization

The results I have just explained in a market with heterogeneous labor rely on the assumption that immigrants and natives in the same skill group are equal and then perfect substitute in production. However, many papers show that immigrants and natives present a small but significant degree of imperfect substitution within education-experience groups (see Ottaviano and Peri 2012 and Card 2009b for the U.S., Manacorda et al. 2012 for the U.K. and D’Amuri et al. 2010 for Germany)³. If we focus on low-skilled immigration, the assumption that natives and foreign-born workers do not compete for the same jobs seems to be reasonable. In fact, while immigrants may likely possess physical or “manual” skills very similar to those of native-born workers, it is quite realistic to imagine that the two groups are not comparable in terms of language, or more generally “communicative”, skills. Therefore, natives may react to the reduction in wage due to the bigger competition in physical jobs by specializing in those tasks in which they have a comparative advantage.

Peri and Sparber (2009) developed a simple theoretical model which well predicts the effect of immigration on natives’ task specialization. In this model, the two authors consider an open economy that produces a single tradable good, combining two non-tradable services (Y_H and Y_L) through a CES production function defined by⁴:

$$Y = \left[\beta Y_L^{\frac{\sigma-1}{\sigma}} + (1 - \beta) Y_H^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (2.5)$$

The final good is the numeraire and it is assembled by perfectly competitive firms, so that

³However, as I will write later, these estimates are not free from defects (see p. 19)

⁴In Equation (2.5), the parameter $\sigma \in (0, \infty)$ measures the elasticity of substitution between Y_H and Y_L while the coefficients β and $(1 - \beta)$ capture the relative productivity of the two intermediate services in the production of good Y .

w_i is equal to the marginal product of the service Y_i . The intermediate service Y_L is provided by the low-educated workers (L), while Y_H by the high-educated ones (H)⁵.

Less-educated workers must perform both manual and communication tasks in order to produce Y_L . According to the definition of Peri and Sparber (2009) manual tasks require physical skills (e.g. dexterity, body coordination, strength), whereas communication tasks require mostly language skills (e.g. directing, training and organizing people). Y_L is produced according to the following CES function⁶:

$$Y_L = \left[\beta_L M^{\frac{\theta_L-1}{\theta_L}} + (1 - \beta_L) C^{\frac{\theta_L-1}{\theta_L}} \right]^{\frac{\theta_L}{\theta_L-1}} \quad (2.6)$$

where M and C are the aggregate units of manual-tasks and communication-tasks, respectively. For simplicity, since Peri and Sparber (2009) focuses only on less-educated workers, they make the assumptions that high-educated workers perform a unique “analytical” tasks and that Y_H is produced by a linear technology equal to the total supply of highly-educated working hours ($Y_H = H$).

Given this context, the relative task demand function is:

$$\frac{C}{M} = \left(\frac{1 - \beta_L}{\beta_L} \right)^{\theta_L} \left(\frac{w_C}{w_M} \right)^{-\theta_L} \quad (2.7)$$

where w_M and w_C denote the compensation paid for one unit of manual and communication task, respectively.

While highly-educated workers are identical from a productive point of view, less-educated ones are heterogeneous and may differ from each other from their relative task productivity. Obviously, less-educated workers are also distinguished between domestic “native-born” workers (D) and “foreign-born” workers (F). The model is based on the assumption that natives and immigrants differ in that the first have a comparative advantage in performing communication tasks. Mathematically, if I define μ_j and ζ_j as the efficiency of worker-type j in manual and communicative tasks respectively, the previous assumption implies $(\zeta_D/\mu_D) > (\zeta_F/\mu_F)$.

Each worker takes the unit compensation paid to tasks (w_M and w_C) as given and then

⁵Peri and Sparber (2009) define as low-educated all workers with a high-school diploma or less and as high-educated all workers with some college degree or more, following the results of the quite abundant literature that finds high substitutability between workers with no degree and those with a high-school diploma and between those with some college education and those with a college degree (see, for example, Goldin and Katz 2007 and Ottaviano and Peri 2008) and a significant degree of imperfect substitutability between workers with a high school diploma or less and those with some degree of education or more (D’Amuri et al., 2010; Ottaviano and Peri, 2008).

⁶In Equation (2.6), the coefficient $\beta_L \in (0, 1)$ captures the relative productivity of manual skills and $\theta_L \in (0, \infty)$ measures the elasticity of substitution between M and C.

chooses to allocate her labor endowment between m_j manual tasks units and c_j communication tasks units in order to maximize her labor income.

$$\frac{c_j}{m_j} = \left(\frac{w_C}{w_M} \right)^{\frac{\rho}{1-\rho}} \left(\frac{\zeta_j}{\mu_j} \right)^{\frac{1}{1-\rho}} \quad (2.8)$$

The equilibrium relative supply of communication versus manual tasks for natives and immigrants in Equation (2.8) depends positively on relative task compensation and on the worker's relative efficiency in performing tasks⁷.

By summing the skills provided by each group, the authors define the aggregate relative supply of tasks in the economy:

$$\frac{C}{M} = \frac{C_F + C_D}{M_F + M_D} = \varphi(f) \frac{C_F}{M_F} + (1 - \varphi(f)) \frac{C_D}{M_D} \quad (2.9)$$

The term $\varphi(f)$ is the share of manual tasks supplied by foreign-born workers ($M_F/(M_D + M_F)$) and is a monotonic increasing function of the foreign-born share of less-educated workers ($L_F/(L_D + L_F)$). Substituting Equation (2.8) in (2.9) and equating relative supply with relative demand in (2.7), the authors obtain the equilibrium relative compensation of tasks:

$$\frac{w_C^*}{w_M^*} = \left(\frac{1 - \beta_L}{\beta_L} \right)^{\frac{(1-\rho)\theta_L}{(1-\rho)\theta_L + \rho}} \left[\frac{\zeta}{\mu} \left(f, \frac{\zeta_F}{\mu_F} \right) \right]^{\frac{-1}{(1-\rho)\theta_L + \rho}} \quad (2.10)$$

The function $\frac{\zeta}{\mu} \left(f, \frac{\zeta_F}{\mu_F} \right)$ is a weighted average of the relative skill endowments among natives and immigrants and it is an aggregate measure of communication versus manual ability in the economy. This function depends: negatively on f because, since immigrants have a comparative advantage in manual tasks, a larger share of immigrants in the economy decreases the average relative communication ability of the workforce; positively on $\frac{\zeta_F}{\mu_F}$ because the lower the relative communication ability of the immigrants, the lower the average of this ability is in the economy.

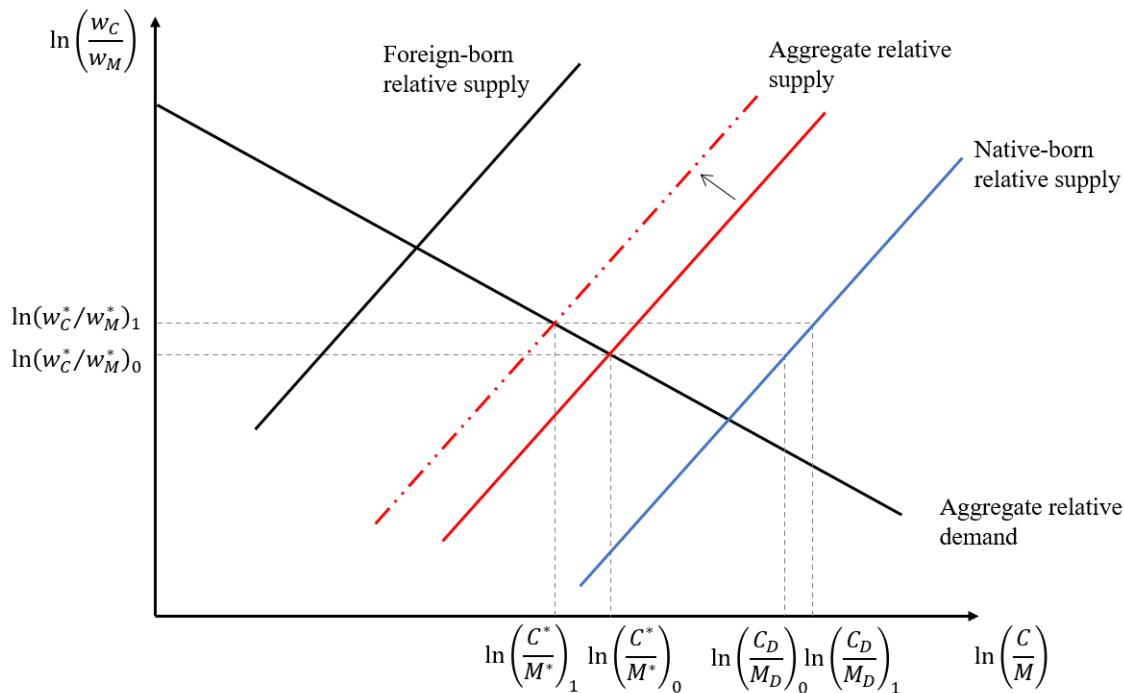
The equilibrium wage uniquely determines the level of the relative supply of tasks for each group. In particular, the aggregate relative provision of tasks for natives and the whole economy are respectively:

$$\frac{C_D^*}{M_D^*} = \left(\frac{1 - \beta_L}{\beta_L} \right)^{\frac{\rho\theta_L}{(1-\rho)\theta_L + \rho}} \left(\frac{\zeta_D}{\mu_D} \right)^{\frac{1}{1-\rho}} \left[\frac{\zeta}{\mu} \left(f, \frac{\zeta_F}{\mu_F} \right) \right]^{\frac{-1}{(1-\rho)\theta_L + \rho} \frac{\rho}{1-\rho}} \quad (2.11)$$

$$\frac{C^*}{M^*} = \left(\frac{1 - \beta_L}{\beta_L} \right)^{\frac{\rho\theta_L}{(1-\rho)\theta_L + \rho}} \left[\frac{\zeta}{\mu} \left(f, \frac{\zeta_F}{\mu_F} \right) \right]^{\frac{\theta_L}{(1-\rho)\theta_L + \rho}} \quad (2.12)$$

⁷The parameter $\rho \in (0, 1)$ is a parameter that enters in the worker's maximization problem and captures the decreasing returns from performing a single task, which implies that no workers will fully specialize.

Figure 2.4: The effects of low-skilled immigration on task specialization



Now the model is set up and I am able to predict theoretically the effects that we want to estimate in the following chapters. Suppose that the economy experiences an increase in the share of immigrants in the population (f).

Prediction 7 Lowering the average relative ability $\xi_{\mu}(\cdot)$, an inflow of low-skilled immigrants has three effect:

1. it increases the return to communication relative to manual tasks (Equation 2.10);
2. the increase in $\frac{w_C^*}{w_M^*}$, in turn, implies an increase in the relative supply of communication tasks by natives (Equation 2.11);
3. it decreases the aggregate relative supply of communication tasks in the economy (Equation 2.12).

Figure 2.4 displays the results of *Prediction 7*. The fact that natives have a comparative advantage in language-intensive tasks implies that the relative task supply curve of immigrants (black line) is to the left of that of domestic workers (blue line). Equation (2.9) states that the aggregate relative task supply (red line) is a weighted average of the natives and immigrants relative supplies. Then, it lies in the between of them, with the distance of it from the two proportional to $\varphi(f)$ and $1 - \varphi(f)$. An increase in f rises the share of manual tasks supplied by the foreign-born workers $\varphi(f)$, moving the red line towards the black one. Since, thanks to the

new immigrants, more manual tasks are provided in the economy, the relative compensation of communication tasks increases from $\ln\left(\frac{w_C^*}{w_M^*}\right)_0$ to $\ln\left(\frac{w_C^*}{w_M^*}\right)_1$, prompting natives to specialize in that kind of occupations. These effects are magnified in the case of an inflow of new immigrants with a $\frac{\zeta_F}{\mu_F}$ lower than that of the immigrants already in the economy.

2.2 Empirical Literature

Theoretical models, even though sensible to the assumptions imposed, reach quite unarguable predictions about the effects of immigration on the host country labor market outcomes. In the last decades, many economists have tried to find confirmations to these predictions in the real world, however without reaching equally indisputable conclusions (for a complete review, see Okkerse 2008 or Edo 2019). Even though based on the same canonical model, the studies coping with the estimation of immigration's labor market effects are often based on very different empirical models. A first distinction can be made which separates studies that use structural and non-structural approaches.

In a few words, structural methods build on a theoretical framework and, after having estimated the main parameters of the model, try to simulate the impact of immigration on wages or employment. Being theory-driven however, the results of this kind of researches are strongly affected by the assumptions of the model or by the lack of it to capture particular characteristics or adjustment processes in the economy. In summary, these studies find evidence that in the long-run the average effect of immigration on wages is either null or even positive. These results depend on the degree of substitution between immigrants and natives estimated: papers that find evidence that immigrants and natives are close substitutes conclude that immigration does not affect wages (Borjas, 2014; Edo and Toubal, 2015); instead, papers that find some degree of imperfect substitution observe a positive effect (D'Amuri et al., 2010; Ottaviano and Peri, 2012; Brücker et al., 2014). However, these last estimates should be taken with a grain of salt, since downgrading and misclassification of immigrants across skill cells may impair them, biasing also the effect of immigration on labor market outcomes (Dustmann and Preston, 2012).

Unlike structural methods, non-structural ones estimate (rather than simulate) the effect of immigration on labor market by exploiting the fact that immigrants are not evenly distributed across geographical areas (*Spatial Approach*) and skill groups (*National Skill-Cell Approach*).

The "spatial approach" is based on the idea that every geographical area (i.e. cities, provinces,

regions) can be seen as a local labour market and that areas with low levels of immigrants can be considered as counterfactuals of those with high levels. The parameter estimated can be interpreted as the overall effect of immigration on employment and average wage level. However, this method does not reach results that unambiguously determine these effects: Altonji and Card (1991) and Jaeger et al. (2018), for example, observe a negative effect on native wages, while Dustmann et al. (2013) find that in UK immigration exerts downward wage pressure below the 20th percentile of the wage distribution (where immigrants are denser), but a positive effect in the upper part of the wage distribution, concluding that the overall effect on wages is positive. A result observed also by Card (2009a). Moreover, this approach is not conceptually flawless: first, it is difficult to understand if the estimates refer to a (presumably negative) short-run effect or instead to a (presumably null or positive) long-run effect (Jaeger et al., 2018); second, the assumption that local labor markets are close is hard to believe since native workers and firms are free to move across areas and then their response may weaken the real effect of an immigrant supply shock (Card, 2001).

In order to not incur in the second conceptual issue of the “spatial approach”, Borjas (2003) developed what is called the “national skill-cell approach”. Instead of exploiting variation between geographical areas, this method uses differences in immigrants penetration among different skill-cell groups (defined in terms of both education and work experience) to estimate the effect of immigration on workers’ outcomes. The advantage of this strategy is that for an individual should be more costly to improve her skills rather than changing area in response to an immigration inflow. Most of these papers agree in concluding that immigrants harm natives’ wages (Borjas, 2003, 2014; Llull, 2017). As regards employment, D’Amuri et al. (2010) find no detrimental effect on natives, but a significantly negative one on old immigrants. However, Dustmann et al. (2016) strongly criticize this approach for two reasons: the first one is that results obtained with the “spatial approach” and those obtained with the “national skill-cell approach” should not be compared because the latter structurally reaches more negative estimates, since it estimates just the direct partial effect of immigrants in the same skill group of natives, without considering the possible cross-effects produced by immigrants in the other groups, as instead the former approach does; the second reason is that the “national skill-cell approach” heavily suffers from the problem of immigrants downgrading (that is the fact that foreign-born workers are usually employed in jobs that are worse than those in which are employed natives with similar skills) and then estimates might be biased since immigrants and natives with the same education and experience are not actually competing for the same jobs.

The “spatial approach”, however, also suffers from another issue. Immigrants, in fact, tend to settle in those areas where economic outcomes are better, arising an endogeneity problem between the share of immigrants and labor market outcomes. Natural experiments exploit the fact that changes in political or historical contexts can trigger immigrants flows independent from the host country economic outcomes. All this kind of papers observe a negative (or at most null) short-run impact of immigration on both wages (Card, 1990; Hunt, 1992; Borjas, 2017) and employment of natives (Hunt, 1992; Angrist and Kugler, 2003; Glitz, 2012). However, Peri (2016) warns about the external validity of these researches, since they are characterized by fast and unexpected inflows of foreign-born individuals, whereas usually immigration happens through slower and more predictable patterns.

A recent branch of the literature has supposed that the previous conflicting results may be due to the fact that host country labor market is able to absorb immigration without experiencing any significant short-run negative impact on natives wages or employment thanks to a series of alternative adjustments. As I have shown in the previous section, one of them can be the possibility that natives react to an increasing number of foreign-born workers by finding occupation in those jobs in which they have a comparative advantage on immigrants and so eluding their competition. As regards immigration and task specialization, the aforementioned paper by Peri and Sparber (2009) is indeed the most important one. Analyzing decennial data for U.S low-skilled workers from 1960 to 2000, they found that a 1% increase in the share of immigrants is associated with a highly significant 0.37% rise in the natives’ relative supply of communication tasks. This result is almost completely explained by an increase in the natives’ provision of language-intensive jobs rather than a decrease in that of physical-intensive ones. Moreover, the authors also find that, differently from natives, long-term immigrants are not able to shift toward more language-intensive occupations, providing support to the theory that sees them as the most vulnerable to the competition with new immigrants (see for example Longhi et al. 2008 and D’Amuri et al. 2010). Finally, this paper shows that immigrants more than compensated the change in skills supply among natives, ensuring an increase in the overall relative manual task supply in the economy (as stated by Equation 1.12) and in the relative wage compensation of communication tasks, which implies a smaller negative wage effect among less-educated natives than that predicted by the models in which natives and immigrants are perfect substitutes.

Amuedo-Dorantes and De La Rica (2011) investigate the same causal effect using Spanish Labor Force Survey data from 2000 to 2008. They observe that also in Spain less-skilled im-

migrants and natives do not appear to be perfect substitutes and, in particular, they find that the effect of immigration on the relative task supply of natives in their research is twice as that found in the United States. Moreover, the Spanish case is really interesting since almost half of the immigrants comes from other Spanish-speaking countries and then, the assumption that natives have a comparative advantage in host country language proficiency relative to those immigrants seems to be invalidated. Authors find that actually Latino immigrants have a lower manual to communicative tasks ratio than non-Latino immigrants, but the large effect they find on the task specialization of natives induces them to conclude that, even if important, language proficiency is not the unique driver of this adjustment process.

De la Rica and Polonyankina (2013) extends the paper by Amuedo-Dorantes and De La Rica (2011) to account for the impact of immigration during the recession years 2008-2012, following the results of Peri (2010) which find evidence that immigration has different consequences in expansionary and recessionary periods. Using Spanish Labor Force data from 2001 to 2012, the authors find that during the expansionary years (2001-2007) natives significantly respond to immigration increasing their occupation in interactive relative to manual-intensive jobs, with no negative effects on the employment rate of natives as well as that of non-recent immigrants. However, the pattern completely changes during recession years. There is no evidence that natives continue to reallocate themselves to different occupations in order to react to immigration inflows. Furthermore, an analysis of employment rates shows that while natives do not suffer any negative effect, non-recent immigrants notably do. This finding can be seen as a further demonstration that new immigrants are more likely to be considered close substitutes of earlier immigrants than of native workers.

D'Amuri and Peri (2014) analyze data of 15 European countries over the 1996-2010 period and they find that a 1% increase in the share of foreign-born workers increases the relative supply of complex (abstract and communicative) relative to simple (routine and manual) occupations by between 0.05 and 0.07%. This labor market adjustment takes place with no detrimental effect on natives' employment rates. In fact, authors find evidence that immigration stimulates hiring with no impact at all on separation rates for natives. Moreover, this paper offers two further interesting findings: first, it finds that, although at a slower rate, the job upgrade did not disappear during the Great Recession period (2007-2010); second, exploiting the differences in the Employment Protection Legislation (EPL) in the 15 countries of interest, it concludes that job reallocation is stronger in low-EPL countries, especially for the less-educated workers.

Another interesting research on the topic is that by Polonyankina (2018). The paper studies immigrants-induced natives reallocation in different stages of the business cycle for 18 Euro-

pean Countries, divided into two groups: West and South Europe⁸ and Middle and East Europe (post-communist economies)⁹. Using the Eurostat Labor Force Survey, the author finds evidence of task specialization for natives in West and South Europe during expansionary years. The effects, however, disappears during the Great Depression. As for post-communist countries instead, no displacement effect of task specialization is found in either stage of the business cycle. The author offers two possible explanations to the difference between the two groups of countries: first, Middle and East countries have a lower number of immigrants than West and South countries; second, the period of the analysis is just after the entrance of these countries in Europe, when their economies have suffered large outflows of natives due to the open European labor market.

Unfortunately, the literature concerning labor market effects of immigration in Italy is not as wide as that for other countries, such as the United States or the UK. But all papers seem to reach the same conclusion, that there is no clear evidence of a negative impact of immigration in this country. More specifically, Gavosto et al. (1999) find a slightly positive impact of immigration on natives wages in the period from 1986 to 1995, mainly driven by that on blue-collar workers. This result is confirmed also by Staffolani and Valentini (2010) who find that immigration significantly rose both white-collars and blue-collars wages in Italy between 1994 and 2004. The conclusions reached by these two papers are not completely surprising since, as already mentioned, wages in Italy are characterized by a sensitive downwardly rigidity. Then following *Prediction 3*, it is more likely that immigration could have affected natives employment rates rather than their wages. However, Venturini and Villosio (2006) find no evidence that immigration has worsened the natives' probability of transition from and to unemployment in the 1993-1997 period. More recently, Fusaro and López-Bazo (2018), analyzing Labour Force Survey data from 2009 to 2017, find no detrimental effect of foreign-born workers on employment rates of natives but a slight one on blue-collar workers. To my best knowledge, there is no paper which analyzes the existence of immigration-induced task specialization in Italy, as I will try to do in this dissertation.

⁸Namely Austria, Denmark, Finland, France, Greece, Ireland, Italy, Norway, Netherlands, Portugal, Spain, Great Britain, Belgium

⁹Namely Slovakia, Czech Republic, Hungary, Romania, Bulgaria

Chapter 3

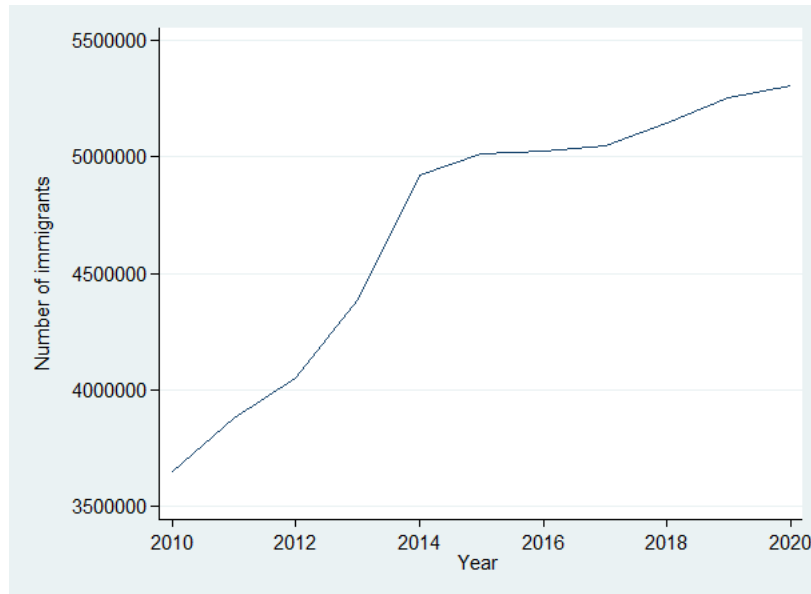
The Research Context and the Empirical Strategy

This chapter starts my empirical analysis which has the purpose of testing whether the main implications of the theoretical model developed by Peri and Sparber (2009) are valid also for the Italian labor market. However, before focusing on my database and on the econometric techniques that I have decided to employ, I chose to report also some telling data about immigration in Italy which could be eventually useful later to better understand the final results. The chapter is then structured as follows: Section 1 contextualizes my research, illustrating the history and the main characteristics of immigration in my country of interest; Section 2 describes the data, in particular the construction of the indices measuring the supply of communicative and manual tasks by individuals, created exploiting the O*NET database; finally, Section 3 explains my empirical strategy for the identification and the estimation of the effect of immigration on natives' task specialization, focusing particularly on the instrument used in order to get rid of the endogeneity problem typical of the spatial approach.

3.1 Immigration in Italy

In Italy, immigration is a quite recent phenomenon, especially if compared with the history of other countries such as the United States, the U.K. or France. For about one century, in fact, Italy actually experienced large outflows of workers, eager to leave their homeland to seek fortune in the U.S., South America or other European countries as well. It has been only during the Seventies, thanks to a flourishing period of economic expansion, that Italy has been able to become the destination of huge flows of foreign-born workers and, as a consequence, to definitely change its status in immigrant-receiving country. In 1981, the first census of foreigners

Figure 3.1: Number of immigrants in Italy, 2010-2020



by Istat revealed the presence of just 210,937 foreign residents in the Italian territory¹, but it was only the beginning of 30 years during which the number of immigrants in the country dramatically increased with no interruptions. Over the Nineties, the dissolution of the Yugoslavia and the Soviet Union, as well as the idiosyncratic position of the country in the middle of the Mediterranean Sea, attracted large inflows of individuals from countries such as Albania, Romania, Morocco and Egypt. In those years, also the minorities coming from some Asian developing countries (among the others, China, Philippines and India) increased their weight in the spectrum of nationalities that were present in the country. Given these circumstances, it was inevitable that in 2001 the number of foreign residents in Italy was exponentially rocketed to 1,334,889 (corresponding to 2.3% of the population)². Immigration didn't stop, so that the number of foreign-born individuals continued to grow up at a high pace also over the first decade of the XXI century: in this period however, the main driver became the enlargement of the European Union to Central and East European countries (e.g. Romania and Bulgaria) which enabled workers of these states to freely enter into the Italian labor market. It was only in 2014 that, after approaching 5 million foreign residents, the growth rate significantly slowed, as shown by Figure 3.1.

According to the Italian Bureau of Statistics (Istat), at the beginning of 2020, the non-Italian regular residents in Italy amount to 5,306,548 individuals (almost 9% of the population)³. Their distribution on the territory is extremely heterogeneous and does not follow a pattern similar

¹Source: <http://seriestoriche.istat.it/>

²Source: <http://seriestoriche.istat.it/>

³Source: <http://dati.istat.it/>

Table 3.1: Immigrants and natives distribution by geographical area

Geographical area	Immigrants	Population
North-West	33.77%	26.75%
North-East	24.05%	19.36%
Center	25.26%	19.90%
South	12.08%	23.05%
Islands	4.84%	10.95%
<i>Observations</i>	<i>5,306,548</i>	<i>60,244,639</i>

Notes: Personal elaboration of Istat data, updated to the 1st January 2020. North-west includes Valle d'Aosta, Piemonte, Liguria and Lombardia; North-East includes Trentino Alto-Adige, Veneto, Friuli-Venezia-Giulia and Emilia-Romagna; Center includes Toscana, Marche, Umbria and Lazio; South includes Abruzzo, Molise, Campania, Puglia, Basilicata and Calabria; Islands includes Sicilia and Sardegna. Immigrants are all people without Italian citizenship.

to that of natives. As can be seen from Table 3.1, in fact, about 83% of immigrants live in Northern and Central Italy, while only 66% of the whole population do. It is evident that while natives tend to be distributed quite evenly among the different Italian macroregions, immigrants tend to be clustered in the richest parts of the country and especially in the big cities (almost 15% of immigrants actually live in just 3 cities: Rome, Milan and Turin).

As previously explained, the results of the theoretical model that this paper wants to test are strictly dependent on the fundamental assumption that natives own a comparative advantage in communicative-intensive jobs with respect to immigrants, thanks to their better language proficiency. This implies that one feature worth to be scrupulously analyzed for the purpose of my dissertation is then the nationality of these foreign-born workers. In this regard, Table 3.2 reports the 10 nationalities with the highest number of immigrants in Italy. It can be seen

Table 3.2: Immigrants by nationality

Country	Share		
1. Romania	22.76%	6. Philippines	3.19%
2. Albania	8.31%	7. India	3.04%
3. Marocco	8.15%	8. Bangladesh	2.79%
4. China	5.75%	9. Egypt	2.57%
5. Ukrain	2.40%	10. Pakistan	2.40%
<i>Observations</i>			<i>5,306,548</i>

Notes: Personal elaboration of Istat data, updated to the 1st January 2020. Immigrants are all people without Italian citizenship. Shares are computed as number of immigrants of a nationality to the total number of observations.

Table 3.3: Immigrants and population distribution by age

Age	Immigrants	Population
16-24 years old	12.19%	11.87%
25-34	23.60%	14.52%
35-44	27.62%	17.57%
45-54	20.36%	21.73%
55-64	11.76%	19.00%
65-74	4.47%	15.30%
Observations	4,250,286	44,745,312

Notes: Data taken from <http://demo.istat.it/>. Only individuals in the working age are considered (16-74 years old). Immigrants are all individuals without Italian citizenship.

that Romanians are by far the most represented nationality (accounting for almost one quarter of foreign-born residents), while other immigrants mainly come from former Communist countries, African countries overlooked on the Mediterranean Sea and East Asia developing countries. It is clear that none of the immigrants coming from one of these countries of origin has Italian as her mother tongue, and actually just a negligible amount (0.6%) of the total number of foreigners has born in a nation in which Italian is an official language⁴. At this point, the unique possible issue concerning language proficiency may actually arise from the fact that the large share of Romanian immigrants in the country is explained by the belonging of Romanian and Italian to the same linguistic family, impling some similarities between the two. However, these languages are not the same and it is more realistic to think that, given this fact, Romanians have a comparative advantage on other immigrants rather than that they don't have a disadvantage with respect to Italians. Given all these considerations, I am quite confident in concluding that the aforementioned assumption holds in the Italian labor market, at least for those immigrants that have not attended school in the country⁵.

Focusing on characteristics more related to the labor market, Del Boca and Venturini (2005) find that Italian immigration is mainly characterized by young and low-skilled individuals. In this regards, Table 3.3 compares the distribution of immigrants and the whole population by age, considering only individuals between 16 and 74 years old. As can be seen, almost 65% of immigrants have an age below 45 years old, whereas only 44% of the entire population does. Another interesting fact is that only 4.47% of immigrants is aged 65 years or more, whereas more than 15% of natives are in the same age group. These results are clearly a consequence of

⁴These nations are namely: San Marino, Città del Vaticano, Malta and also some parts of Switzerland, Slovenia and Croatia.

⁵However, unlike the other papers on the argument which use more detailed data, I am not able to distinguish recent and non-recent immigrants.

Table 3.4: Immigrants and natives distribution by education level

Educational Level	<i>Age</i> ≥ 15		15 ≤ <i>Age</i> ≤ 34	
	Natives	Immigrants	Natives	Immigrants
Elementary school Diploma or less	16.71%	10.44%	0.68%	6.96%
Middle school Diploma	31.34%	44.58%	33.07%	52.03%
High school Diploma	36.64%	33.97%	48.14%	32.21%
College degree	15.30%	11.01%	18.11%	8.79%
Observations	47,787,470	4,205,952	10,893,174	1,510,991

Notes: Personal elaboration of Istat data, updated to the 1st January 2020. Immigrants are all individuals without Italian citizenship.

the fact that immigration in Italy is a recent phenomenon: people, indeed, tend to migrate when they are young and since this phenomenon began to be huge just 40 years ago in this country, it is normal that the share of foreigners in the oldest cohorts is very low. Given this distribution of foreign-born individuals by age, it is likely that will be the younger cohorts those most affected by the immigrants-induced competition.

Table 3.4, instead, reports the distribution of immigrants and natives divided by educational level. Considering all the individuals with an age above 15 years old, immigrants seem to be less educated than Italians, but the difference is really slight. In particular, 15.30% of natives owns a college degree, whereas 11% of immigrants does. Moreover, natives have also a greater share of individuals with a high school diploma, though they show a larger share of individuals with an elementary school diploma or less too. This is clearly due to the fact that this definition of natives includes also very old cohorts, which probably have attended school when mandatory educational attainment was very short, whereas I have previously shown that immigrants are heavily more concentrated in more recent ones. For these reasons, I perform the same analysis considering only individuals with an age between 15 and 34 years old. As I expected, natives significantly improve their educational levels, whereas those of immigrants remain quite stable (if not even worse). Natives show a share of high-skilled individuals more than twice as larger as that of immigrants, and also among low-skilled the former report an educational level significantly higher than the latter.

Obviously, all the data seen so far refer only to regular immigrants, but illegal immigration is also a widespread phenomenon in Italy. On the 1st January 2014, 350 thousands of individuals were estimated to be irregularly present on Italian territory, while just 4 years later this number dramatically rose to 533 thousands⁶. Indeed, those years have been an incredible period of

⁶Source: <https://www.ismu.org/chiarimenti-numero-immigrati-irregolari/>

illegal immigration, especially through the Mediterranean Sea: from 2014 to 2019, 659,588 people landed on Italian coasts. Even though irregular, many of these immigrants actually have a job, in particular in the agricultural sector or as domestic workers and caretakers⁷. This situation may affect my estimation of the effect of immigration on the task specialization of natives because illegal immigrants are not actually considered in the computation of the share of immigrants in a specific area but, since they could be employed in some kinds of job, they represent an effective supply shock in that local labor market.

3.2 Data

3.2.1 Istat Labour Force Survey

My main dataset for this research is the Labor Force Survey (“Rilevazione delle Forze di Lavoro” in Italian) provided by the Italian National Bureau of Statistic (Istat). The LFS is a continuous survey which collects data of a sample composed of people with an age of at least 15 years and the other components of their families, on a quarterly base. It is useful for my analysis since it provides data about the main aggregates of the labour market (occupational status, type of job, work experience, etc.), disaggregated by the main socio-demographic characteristics⁸.

Unfortunately, Istat does not provide non-public datasets to students, so that the only data in which the province of residence of the individual (a fundamental variable that I will use later for my specifications) is available are those starting from 2014. As a consequence, I am forced to use cross-sectional LFS for the period 2014-2019 for my purpose. Merging these datasets I obtain more than 2 million observations. However, since I am interested only in those individuals who have a job (and for which I should be able to measure the relative supply of communication tasks), I drop individuals not in the working-age (i.e. below 16 years old and above 74 years old) and those unable to work or temporarily unemployed. At this point, what I have is a database of 774,216 observations.

3.2.2 O*Net Database

The LFS database provides a lot of interesting information about the occupations and the most relevant characteristics of the Italian workers. However, since my research aims to investigate

⁷Source: https://www.interno.gov.it/sites/default/files/2020-08/dlci_-_analisi_dati_emersione_15082020_ore_24.pdf

⁸Source: <https://www.istat.it/it/archivio/127792>

whether immigration pushes natives towards more communicative-intensive jobs, I need specific data about the skill-content of their diverse occupations. For this purpose, the most helpful source of data is undoubtedly the O*NET Database provided by the U.S. Department of Labor⁹.

The Occupational Information Network (O*NET) is a free online “database of occupational characteristics and worker requirements information across the U.S. economy”¹⁰. For each job, it provides a plethora of information such as workers requirements (i.e. skills, knowledge and education required to perform the job), workers characteristics (i.e. abilities, interests and values needed to perform the job), experience requirements (i.e. the training and licensing level needed for the work), the job requirements (i.e. the work activities and context involved in the job) and other information about the labour market of the different jobs (e.g. the occupational outlook and the salaries). I create my measure of job task-intensities using the O*NET survey related to the abilities required by each job. This dataset assigns a numerical value between 1 and 5 to describe the importance of 52 distinct employee abilities for each of the 968 occupations defined by O*NET. Since these measurements are based on U.S. labor market characteristics, I use them under the assumption that occupations in the United States and in Italy are not that different with regards to their manual as opposed to communicative task content.

Table A1 in the Appendix lists each of these 52 O*NET variables and organizes them into the categories that I will use to construct the manual and communication supply indices. For comparability reasons, I follow Peri and Sparber (2009) and construct both a “basic” and an “extended” definition of manual and communicative abilities. In the basic definition, the manual intensity index is computed by averaging just those abilities involving “movement and strength” while the communication intensity one considers only measures related to, both oral and written, expression and comprehension. Under the extended definition instead, the manual intensity index includes also “sensory and perception” abilities (such as measures of general, visual and hearing perceptions), while the communication intensity index adds also “cognitive and analytical” and “vocal” abilities to those already used in the basic definition. As explained by the aforementioned authors, the basic definitions are preferable since they fit better the notion of manual and communicative abilities. However, allocating O*NET abilities variables into a simple manual versus communicative job requirements categorization implies a series of arbitrary choices and then performing my analysis with both these definitions can be used as a robustness check for the validity of such a framework.

Unfortunately, the O*NET database classifies the different professions using a personalized

⁹Specifically, in this dissertation I will use the 25.0 version of this database, publicly available at <https://www.onetcenter.org/database.html>

¹⁰Source: <https://www.dol.gov/agencies/eta/onet>

Table 3.5: Occupations and relative task intensities

Occupation (2-digit ISCO08-code)	Comm. intensity index	Manual intensity index	C/M index	Share of imm. in workforce
<i>a) Four occupations with the highest communication/manual intensity</i>				
24. Business and administration professionals	0.960	0.431	1	1.05%
26. Legal, Social and Cultural Professional	0.997	0.473	0.980	3.25%
12. Administrative and commercial managers	0.972	0.453	0.961	2.70%
41. General and keyboard clerks	0.941	0.464	0.913	1.24%
<i>b) Four occupations with the lowest communication/manual intensity</i>				
81. Stationary plant and machine operators	0.713	0.958	0.335	14.77%
93. Labourers in mining, construction, manufacturing and transport	0.694	0.940	0.333	20.88%
91. Cleaners and helpers	0.618	0.838	0.331	36.98%
92. Agricultural, forestry and fishery labourers	0.690	1	0.309	30.94%

Notes: Personal elaboration based on O*NET task definitions and LFS data for the period 2014-2019. Basic definitions of both manual and communication intensity indices are used. Basic definition of manual intensity index consists of the average of 19 O*NET variables that capture the intensity of physical abilities, while the basic definition of communication intensity index is the average of 4 variable measuring oral and written comprehension and expression. More detail about the construction are in the Appendix. Indices are normalized so that they can reach at most a value of 1. The share of immigrants in the workforce is computed as the number of non-Italian workers over the total number of workers in a specific occupation, using LFS data for my period of analysis.

codification, which is inevitably inconsistent with that used by Istat. Through the use of adequate crosswalks¹¹, I converted this particular occupation classification into the 3-digit ISCO-08 codes, the one used in the Istat LFS. After this procedure, I compute the communication and manual-intensity indices as well as their ratio for each job. As already said, the O*NET abilities measures assume only values between 1 and 5. In order to account for this rather arbitrary range of values, I rescale these three indices by dividing each of them by the respective maximum value of the index, so that they can reach at most the value of 1. Finally, I merge the O*NET abilities database with the Italian LFS.

Table 3.5 reports the four occupations with the highest and the lowest C/M index using 2-digit ISCO-08 codes, in order to have a broader representation of jobs. To obtain that, I aggregated the 3-digit codes through a weighted average, where the weights are given by the number of workers in the LFS employed in each job. As it can be seen, all the occupations

¹¹Firstly, I created a crosswalk which converts O*NET-SOC19 codes to SOC2018 codes (crosswalk available at https://drive.google.com/drive/folders/1IeKxFmXc9AE18103_oUIIdNciQB20cYUn?usp=sharing); secondly, I converted SOC2018 codes into SOC2010 codes using the crosswalk provided by U.S. Bureau of Labor Statistics and available at https://www.bls.gov/soc/2018/crosswalks_used_by_agencies.htm; lastly, I converted the SOC2010 codes into 4-digit ISCO-08 codes using the crosswalk used also by Hardy et al. (2018) and available at <https://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/> and then I collapse them into the 3-digit ISCO-08 codes, which is the classification of occupations used in the Istat LFS.

Table 3.6: Some individual descriptive statistics

	Natives	Immigrants
Male	56.12%	53.02%
Educational level:		
- <i>Elementary school diploma or less</i>	2.87%	8.34%
- <i>Middle school diploma</i>	27.86%	39.94%
- <i>High school diploma</i>	47.64%	40.21%
- <i>College degree</i>	21.52%	11.50%
Age (mean)	45.39	41.35
Relative task intensity index $\frac{C}{M}$ (mean)	0.536	0.382
Relative task intensity index $\frac{C}{M}$ (std. dev.)	(0.204)	(0.132)
Observations	697,037	77,179

Notes: Personal elaboration of data from Istat LFS in the period 2014-2019 and O*NET abilities survey.

with the highest C/M index require a high level of language proficiency, since the interaction with colleagues and clients, as well as a good knowledge of laws and other national rules, represent fundamental components in their execution. On the other hand, the four occupations with the lowest C/M index are all extremely physical and moreover do not demand specific intellectual capabilities. The results of Table 3.5 are extremely important since they corroborate my definitions of communicative and manual-intensity indices as good proxies for the supply of communicative and manual tasks by the individuals.

Furthermore, in the last column of the table, I report the share of immigrants on the total number of workers performing each of those occupations. Considering that in the Italian LFS the percentage of immigrant workers between 16 and 75 years old is about 10%, it is clear that manual-intensive jobs attract a relatively greater number of foreign-born workers than communicative-intensive ones, which is another result in line with what I expected.

3.2.3 Descriptive statistics

Table 3.6 shows some descriptive statistics about the individuals in my sample of analysis, discriminated between natives and immigrants. In my data, immigrants are significantly less educated than Italians: in fact, almost 50% of them have at most a middle school diploma against 30% of Italians; the latter show also a higher percentage of high school (48% vs. 40%) and college graduates (22% vs. 12%). As in the population, immigrants are also younger than natives and more precisely they are on average younger by 4 years. As far as the kind of occupation is concerned instead, another important insight of the table is that immigrants are clearly

Table 3.7: Some province-year cell descriptive statistics

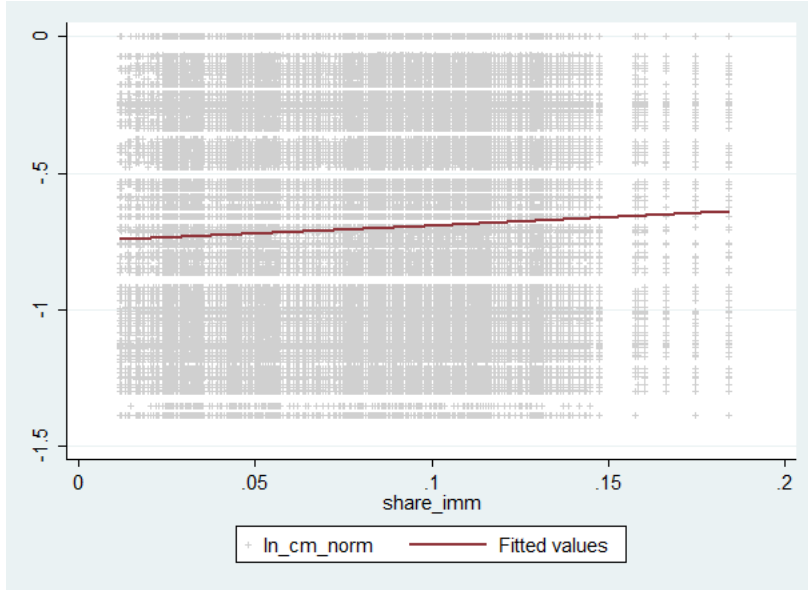
	Mean	Std. Dev.	Min.	Max.
Share of immigrants	8.84%	3.25%	1.15%	18.40%
Relative task intensity index $\frac{C}{M}$	0.514	0.023	0.456	0.591
Unemp. rate	11.91%	5.95	2.89%	31.45%
Pop. density (pop/km ²)	263	380	0.324	2653
GDP level in 2014 (in million Euro)	15,018	22,265	963	160,166
Mean wage (in Euro)	1287	90.68	931	1533
Share of workers in industry	26.26%	8.92%	8.98%	51.17%
Share of workers in services	68.27%	7.86%	46.65%	86.16%
Observations				648

Notes: Personal elaboration of data from different database: data concerning share of immigrants, unemployment rate and population density come from Istat online database; data about GDP level in 2014 come from Eurostat online database; data about mean wage, share of worker employed in industry sector and share of workers employed in services sector are personal computation based on Istat LFS from 2014 to 2019; data concerning relative task intensity index are personal computation based on O*NET abilities survey.

employed in jobs relatively less communicative-intensive than natives, as can be seen from the fact that the average $\frac{C}{M}$ is lower for the former than for the latter. Moreover, the standard deviation of this particular variable is lower for immigrants, implying that they are more concentrated in manual-intensive occupations, whereas natives seem to be more widespread along the occupational spectrum.

The dataset contains also a group of variables, measured at the province level, which are useful to analyze how local labor markets differ among each other during my period of analysis. The most important variable to consider is obviously the share of immigrants in a province, which on average is 8.84%. However, as already seen in Section 3.1, immigrants follow a distribution very different from that of natives and this fact is reflected also by the enormous difference between the minimum and the maximum value of the variable: in 2014 the province of Medio Campidano in Sardegna has a share of immigrants of just 1.15%, whereas in the province of Prato in 2019 this share was 18.40%. This great heterogeneity among local labor markets is highlighted also by the other variables reported and, in particular, this contrast is extremely significant between the North and the South of the country. As regards unemployment, for example, if I consider only North and Central Italy the average unemployment rate among local labor markets is 8.34%, whereas in South Italy this rate is 18.22%. The same pattern can be seen analyzing the composition of the workforce by sector of employment: in northern and central local labor markets on average the 30% of the workers are employed in the industry sector, while in the South only 20% do, since agricultural and services sectors (especially the public one) have in fact a relatively higher weight in the latter (Istat, 2019).

Figure 3.2: Share of immigrants and relative C/M task supply of all natives



At this point, a first rough analysis can be done, using the individual relative communicative tasks supply and looking at whether a correlation with the share of immigrants in the province of the individual exists. Figure 3.2 depicts the scatter plot for all natives where on the x-axis is represented the logarithm of the normalized C/M index and on the y-axis is the share of immigrants in the province. The red line depicts the fitted values line of the regression between these two variables. As can be seen, this line is upward-sloping, showing the presence of a positive correlation between the share of immigrants in a province and the supply of communicative to manual tasks by the individuals in that area (specifically, the correlation is 0.05). However, the fundamental lesson from econometrics is that correlation does not imply causality. Therefore, this primitive analysis should be taken with a grain of salt.

3.3 Empirical Strategy

I have concluded my theoretical analysis in Chapter 2 by explaining the two key equilibrium conditions of the model, expressed by Equations (2.11) and (2.12). These equations demonstrate that theoretically a relationship between the share of immigrants and the workers' relative supply of tasks in a local labor market exists. Following the example of Peri and Sparber (2009), by log-linearizing them, it is simple to obtain the two linear empirical specifications that follow:

$$\ln\left(\frac{C_D}{M_D}\right)_{pt} = \gamma f_{pt} + \alpha_p^D + \alpha_t^D + \varepsilon_{pt}^D \quad (3.1)$$

$$\ln\left(\frac{C}{M}\right)_{pt} = \gamma^{TOT} f_{pt} + \alpha_p^{TOT} + \alpha_t^{TOT} + \varepsilon_{pt}^{TOT} \quad (3.2)$$

The dependent variables of these regressions, $\frac{C_D}{M_D}$ and $\frac{C}{M}$, are the relative supply of communicative versus manual skills provided by native (“domestic”) workers and in the local labor market, respectively, while the share of immigrants in the local labor market (f_{pt}) represents my variable of interest. In Equation (3.1), γ is defined as $-(1/[(1-\rho)\theta_L + \rho])(\rho/(1-\rho)) \times (\partial \ln(\zeta/\mu)/\partial f)$. According to *Prediction 7*, I will expect this coefficient to be positive since an increase in the share of immigrants in the labor market causes natives to specialize themselves into more communicative-intensive jobs in order to escape the increased immigrant-induced competition. In Equation (3.2), instead, $\gamma^{TOT} \equiv (\theta_L/[(1-\rho)\theta_L + \rho]) \times (\partial \ln(\zeta/\mu)/\partial f)$. The sign of this coefficient, however, is more difficult to determine *a priori*: as shown in Figure 2.4, the theoretical model forecasts a negative effect of immigration on the aggregate relative supply of communicative tasks in the economy, due to the bigger supply of manual skills provided by immigrants. But what is represented in Figure 2.4 is just a partial equilibrium: the model developed by Peri and Sparber (2009) does not allow the natives’ supply curve to move in response to the increasing competition; if instead natives react to immigration by augmenting their relative supply of communicative tasks regardless of the wage level (for example, by increasing ζ_D/μ_D) and then shifting their supply curve towards right, a positive effect is actually possible. Besides, each regression contains both time ($\alpha_t^D, \alpha_t^{TOT}$) and province fixed effects (α_p^D, α_p^D). The former account for possible common time-varying technological parameters and represent the term $(\rho\theta_L/[(1-\rho)\theta_L + \rho]) \times \ln((1-\beta_L)/\beta_L)$ from Equations (2.11) and (2.12); the latter, instead, account for variation due to unobserved characteristics of the population, including the term $(1/(1-\rho)) \times \ln(\zeta_D/\mu_D)$. Finally, ε_{pt}^D and ε_{pt}^{TOT} represent the noncorrelated zero-mean error terms of the regressions.

Unfortunately, there are two basic differences between my data and those used by Peri and Sparber (2009), which significantly undermine my possibility of successfully implement such specifications. The first one is that Peri and Sparber (2009) exploit U.S. Census data for their analysis, so that their database coincides with the American population, whereas the Italian LFS is by construction just a representative sample. On this ground, my dependent variables would inevitably suffer from sample variability in these regressions since they would not be exact measures of the relative communicative task supply in each province-year cell, but just estimates that would be significantly affected by the observations composing each specific subsample. This could be a minor problem if the LFS sample is well-constructed, since in that case also the observations in each cell should consequently be a representation of the population of

that specific province in that specific year, so that even if subjected to sample variability those estimates should be on average equal to the actual value. However, as I have explained in Section 3.2.1, for the purposes of this dissertation I am forced to operate a series of “cuts” to my starting database and therefore there is no certainty that, after these operations, the observations which remain in each cell are actually representative of the real population in that subgroup. As a consequence, there are no evidence that aggregating individual task supplies I actually obtain a non-distorted value of my indices and hence the best solution is running these regression with the dependent variable measured at the individual level.

The second issue instead is connected with the instrumental variable, which will be explained in the next section. In a few words, running the first stage regression including province fixed effects, my instrument is not statistically correlated with the share of immigrants in a local labor market (my dependent variable), a result that is quite strange. The problem seems to be that the province fixed effects capture all the variability in the actual share of immigrants, making all the other variables not statistically significant. To solve this problem, I decide then to run the first stage regressions including fixed effects at the region level and then controlling for some province characteristics that should be rather constant over time. In particular, I control for the unemployment rate, the population density, the GDP level in 2014, the mean wage and the share of workers employed in both the industry and the services sector in the province¹².

After these modifications, my specifications have therefore become as follow:

$$\ln\left(\frac{C_D}{M_D}\right)_{ipt} = \delta f_{pt} + X'\beta + \alpha_t^D + \alpha_r^D + W'\lambda + \varepsilon_{ipt} \quad (3.3)$$

$$\ln\left(\frac{C}{M}\right)_{ipt} = \delta^{TOT} f_{pt} + X'\beta^{TOT} + \alpha_t^{TOT} + \alpha_r^{TOT} + W'\lambda^{TOT} + \varepsilon_{ipt}^{TOT} \quad (3.4)$$

where X' is a set of individual controls (and specifically it includes a dummy for the gender of the individual, a dummy for each decennial age group¹³ and a dummy for each education level¹⁴), α_r are the region fixed effects, while W' is the set of province controls previously de-

¹²Data relative to unemployment rate and the population density are from <http://dati.istat.it>; data about the GDP level in 2014 are from <https://ec.europa.eu/eurostat/data/database>; data related to mean wage, share of workers employed in the industry sector and share of workers employed in the services sector are personal elaborations of the Istat LFS.

¹³The regression includes 5 dummies corresponding to 5 different age groups: 25-34, 35-44, 45-54, 55-64, 65-74 years old. Stata automatically drops the dummy corresponding to the 16-24 years old age group for collinearity problems.

¹⁴Regressions in which all natives are considered include 5 dummies corresponding to 5 different education levels: “Elementary school diploma”, “Middle school diploma”, “3-years high-school diploma”, “5-years high school diploma” and “College degree”. Regressions which consider low-educated natives only include 4 dummies, that are the aforementioned but obviously “College degree”. Stata automatically drops “No title” dummy for collinearity problems.

scribed. Moreover, for each equation, I also evaluate if immigration has a stronger relationship with the average supply of manual (M^D) or communicative (C^D) tasks of the natives by estimating the following specifications:

$$\ln(M_D)_{ipt} = \delta^M f_{pt} + X' \beta^M + \alpha_t^M + \alpha_r^M + \varepsilon_{ipt}^M \quad (3.5)$$

$$\ln(C_D)_{ipt} = \delta^C f_{pt} + X' \beta^C + \alpha_t^C + \alpha_r^C + \varepsilon_{ipt}^C \quad (3.6)$$

Just as a matter of comparability, I implement also the counterparts of Equation (3.1) and (3.2) using region fixed effects corrected by province controls:

$$\ln\left(\frac{C_D}{M_D}\right)_{pt} = \gamma f_{pt} + \alpha_t^D + \alpha_r^D + W' \tau + \varepsilon_{pt}^D \quad (3.7)$$

$$\ln\left(\frac{C}{M}\right)_{pt} = \gamma^{TOT} f_{pt} + \alpha_t^{TOT} + \alpha_r^{TOT} + W' \tau^{TOT} + \varepsilon_{pt}^{TOT} \quad (3.8)$$

To take into account the different dimensions of the Italian provinces, in these last two equations I use WLS, with weights given by the number of observations in each province-year cell.

As already explained in Chapter 2, another major issue related to specifications based on a “spatial approach” is that the assumption that local labor markets are closed is rather weak. Workers and firms are actually completely free to move across Italian provinces in response to a labor supply shocks and this fact may significantly lower the estimate of the effect of immigration on task specialization of natives. In this regards, Venturini and Villosio (2006) report some data telling that internal mobility across provinces is very limited in Italy. In this dissertation, since there is no availability of data to construct a measure of the net migration rate at the province level which considers only natives to include in my specifications, I solve this problem by dropping all the observations in the Italian LFS who had changed their province of residence in the previous year for work-related reasons (9,101 individuals out of 783,317).

3.3.1 Instrumental variable

A second important problem I have previously talked about is the fact that immigrants are not randomly distributed among local labor markets. More precisely, in my research context it could be the case that unobserved province-specific technology and demand factors have affected the productivity of communicative-intensive jobs, inducing natives to change their occupation and in turn attracting immigrants into a local labour market. These elements are therefore included in the error term (ε) and make my variable of interest potentially endogenous.

In these situations, the most common way to get rid of the endogeneity problem (and the related distortion in the OLS estimator) is to rely on an Instrumental Variable strategy (IV), and in particular I will use the Two-Stage Least Square procedure (2SLS). In the immigration economics literature, the most used instrument is by far the so-called “past settlement” or “enclave” instrument (Jaeger et al., 2018). This instrument exploits the fact that immigrants have been observed to have the tendency of settling in those cities in which the presence of foreigners is already large. Altonji and Card (1991) were the first to use this specific kind of shift-share instrument to identify the causal effects of immigrants on natives’ labor market outcomes by using only the geographic distribution of all immigrants. Later, Card (2001) refined the instrument by exploiting not simply the fact that immigrants choose to live where other immigrants are, but more specifically that they look for other immigrants from the same country of origin. In particular, in this dissertation I follow Card (2009b) and define my “past settlement” instrument as:

$$\tilde{f}_{pt} = \frac{1}{L_{pt}} \sum_o \frac{F_{opt^0}}{F_{pt^0}} F_{ot} \quad (3.9)$$

where F_{opt^0}/F_{pt^0} is the share of immigrants from the country of origin o in local labor market p at time t^0 (which is a time before t), F_{ot} is the number of immigrants from that country of origin at time t at the national level and L_{pt} is the total population in the local labour market p at time t . In other words, the expected share of immigrants in a local labor market is computed as if the actual number of immigrants from each country of origin in the country would have the same distribution among local labor markets that it had in a sufficient distant point in time. In this context, the choice of each foreign-born worker does not depend on the economic outcomes or specific labor demand shocks, but only on the presence of other workers from the same country in the province.

The great appeal of this instrument is that it computes immigration shares at the local level by exploiting the number of immigrants at the national level, which are supposedly less endogenous with regards to local conditions. However, the exogeneity of the national immigrants level to province-specific labor conditions is not a warranty of the fact that the instrument is uncorrelated with the error term and then meets the exclusion restriction. In fact, Equation (3.9) is not only a function of F_{ot} but also of the local immigrant shares F_{opt^0}/F_{pt^0} : if the latter are correlated with such labor market conditions, even if the former are exogenous, the instrument cannot be considered as a valid one. This could be the case if local demand shocks are serially correlated, leading to a correlation between the immigrant shares used in the construction of the instrument and subsequent demand shocks. But this kind of issue can be easily addressed by

choosing settlement patterns that are sufficiently lagged.

As regards the choice of the lag, I use the year 2003 as t^0 for the creation of my shift-share instrument for the period 2014-2019. 2003 is the first year for which Istat provides data about foreigners disaggregated by province and country of origin¹⁵ and therefore it is the moment most distant in time from my period of analysis. Furthermore, 2003 predates the enlargements of the European Union towards some former communists Eastern Europe countries (including Poland, Bulgaria and above all Romania) which happened in 2004 and 2007 and allowed immigrants from these countries to freely enter the Italian labor market. These relevant historical changes may indicate that past and current shocks are unlikely to be correlated, supporting the validity of the exclusion restriction.

Unfortunately, the choice of a lag sufficiently distant in time has not only advantages. In 2001 and 2004, two major reforms established 7 new provinces which become operative only in 2005 and 2009 respectively, so that the number of provinces in 2003 and 2014-2019 were not coincident. These 7 new territories were actually formed through the detachment of some municipalities from the territory of other provinces¹⁶. Since these new territories did not exist in 2003, I don't have data about immigrants in these provinces in order to compute the "share" part of the instrument ($F_{op}^{t^0}/F_{or}^{t^0}$). Luckily, Istat provides data on the total population by province for the period 2002-2010 which are built on the base of the 2011 Census data. In these data, the new provinces are considered, so that an estimate of the population of these provinces in 2003 is actually available. Using these data, I am able to impute the number of immigrants by country of origin to the new provinces. For example, I know that in 2003 the provinces of Medio-Campidano and Carbonia-Iglesias (if operative) would have counted for about 13% and 17% of the population of the "old" province of Cagliari, so that the future "new" province of Cagliari (the one existing since 2005) would have accounted for the remaining 70%. Using these weights, I am able to divide the immigrants of the "old" province of Cagliari disaggregated by country of origin among the three provinces corresponding to that territory in 2014 and also to compute the "share" part of the instrument for all the other new provinces existing in 2014, in the same way. In 2017, however, a further reform occurred by which the province of Olbia-Tempio returned under the jurisdiction of the province of Sassari, while the province of

¹⁵Source: <http://dati.istat.it/>

¹⁶In particular: the province of Monza-Brianza was created with municipalities all coming from the province of Milano, the province of Fermo with municipalities from the province of Ascoli-Piceno, the province of Barletta-Andria-Trani with municipalities from the province of Bari, the province of Ogliastra with municipalities from the province of Nuoro, and the provinces of Carbonia-Iglesias and Medio-Campidano with municipalities of the province of Cagliari. The last new province, Olbia-Tempio, was actually formed with 24 municipalities from the province of Sassari and 2 municipalities from the province of Nuoro; I consider this new province as a former part only of the province of Sassari.

Table 3.8: First stage regressions

	(1)	(2)	(3)	(4)
	f_{ijt}	f_{ijt}	f_{jt}	f_{jt}
\tilde{f}_{jt}	0.405*** (0.053)	0.406*** (0.054)	0.405*** (0.053)	0.406*** (0.054)
Ind. controls	Yes	Yes	No	No
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-statistic	58.67	56.74	58.59	56.57
Observations	697,037	774,216	648	648
R^2	0.905	0.904	0.905	0.904

Notes: Dependent variables in the first row. The explanatory variable is the shift-share instrument computed with 2003 as base year. Specification (1) and (2) use individuals as observational data. The dependent variable in these specification is the share of immigrants each individual faces in her province-year cell. Specification (3) and (4) use province-year cells as observational units. In these specifications, the dependent variable is the share of immigrants in the province-year cell and the coefficients are computed with WLS, using the number of observations in each province-year cell as weights. Specification (1) and (3) includes only native individuals, whereas specification (2) and (4) includes both native and foreign-born individuals. Individual controls include a dummy for the sex of the individual, a dummy for each decennial age group and a dummy for each education level. Province controls include the unemployment rate, the population density, the Gdp in 2014, the mean wage, the share of workers employed in the industry sector and the share of workers employed in the services sector in each province-year cell. Region and year fixed effects are included in all specifications. Standard errors clustered at the province level are reported in parenthesis.

*, **, ***: coefficient significant at 10%, 5% and 1% level, respectively.

Ogliastra returned to be part of the province of Nuoro. Moreover, the territory of the provinces of Cagliari, Medio-Campidano and Carbonia-Iglesias was split into two provinces (Cagliari and Sud-Sardegna) without following any previous border among these provinces. For simplicity, since this territory coincides with the province of Cagliari existing in 2003 (for which I know the distribution of immigrants by country of origin), I consider these two provinces as one starting from 2017¹⁷.

For the computation of the instrument, I used all the 187 nationalities that were present in Italy in 2003¹⁸.

Before using the instrument for my analysis purposes, I test whether it meets the relevance condition by running the first-stage regressions (Table 3.8). Column (1) and Column (2) show coefficients of regressions related to Equation (3.3) and Equation (3.4) respectively, whereas

¹⁷In this way I have 4 provinces (Medio-Campidano, Carbonia-Iglesias, Ogliastra and Olbia-Tempio) with only 3 observations in the period 2014-2019. The remaining 106 Italian provinces (even if some of these with different extension) are observed for the entire period, summing up to 648 observations.

¹⁸In this case too, I have little discrepancies in the classification of immigrants by country of origin between 2003 and 2014-2019: in fact, in 2014-2019 database I consider Serbia, Montenegro and Kosowo as Serbia and Montenegro, and “Recognized non-citizens (Latvia)” together with Latvia.

Column (3) and (4) show those related to Equation (3.7) and (3.8). The results for these specifications are similar since the unique difference between the two pair of regression is the introduction of the controls related to the individual characteristics, which obviously have a negligible effect on the share of immigrants. As it can be seen, with these specifications the endogenous variable and the instrument always show a positive and statistically significant at the 1% level relationship, both in the regressions which use individual and those which use province-year cells as observational units. The coefficients do not change also by considering immigrants, as well as natives, as I did in Columns (2) and (4). Moreover, all the F-statistics are by far above the typical threshold of 10 suggested by Stock et al. (2002) and therefore the instrument can be considered not weak.

Given these results, I can conclude that the instrument is for sure relevant. However, this might be also a problem in the case of a shift-share instrument, since as analyzed by Jaeger et al. (2018) “[i]f the instrument is “too strong” it is highly unlikely to meet the exclusion restriction for a valid instrument and actually separate the endogenous component of the immigrant inflows from the exogenous component. The flipside of this argument is that the prospects to satisfy the exclusion restriction may be better in settings in which the first-stage link is weaker because immigrant inflows have been less stable over time”. However, this is not my case since an F-statistic of 50 is not large enough to consider the instrument “too strong” at all.

Chapter 4

Results

4.1 Immigration and the relative task supply of natives

In this section, I proceed by testing the equilibrium condition expressed in Equation (2.11), that is the effect of immigration on the relative supply of communicative tasks by natives ($\frac{C_D}{M_D}$). To do this, I estimate Equation (3.3) and (3.7), using both OLS and 2SLS and clustering standard error by provinces. Moreover, for each regression, I also study whether immigration has a larger effect on manual or communicative task supplies, by using specifications of the type shown in Equation (3.5) and (3.6). For this first analysis, all the specifications use the basic definitions of both communicative and manual intensity index, since they fit better the notions of this kind of abilities¹.

Columns (1) and (2) of Table 4.1 present respectively the OLS and the 2SLS estimates of δ , δ^M and δ^C , computed using data about native-born workers measured at the individual level (697,037 observations). Looking at these coefficients, two results immediately leap to the eye. First, the estimates of δ strongly confirm what theoretically predicted by *Prediction 7*, as the coefficients are always positive and statistically significant at the 1 percent confidence level. In particular, the OLS estimate suggests that a 1 percentage-point increase in the share of immigrants is associated with a 0.48 percent increase in the relative supply of communicative versus manual tasks among natives. Second, this relative increase is mostly due to a decrease in the supply of manual tasks, rather than to an increase in the supply of communicative skills. The estimates of δ^M and δ^C in Column (1), in fact, show that the former counts for more than three quarters of the value of δ , while the latter just for the remaining part. More precisely, a 1 percentage-point increase in the share of immigrants is associated with a 0.37 percent decrease in the supply of manual tasks by Italian workers, whereas the same variation in the share of im-

¹Table A1 in the Appendix shows the variables used for the creation of these different indices.

Table 4.1: Effect on natives task supply (using basic definitions)

Estimator	(1) OLS	(2) IV	(3) WLS	(4) IV
$\ln(\frac{C_D}{M_D})$	0.480*** (0.102)	0.715*** (0.149)	0.567*** (0.129)	1.285*** (0.218)
$\ln(M_D)$	- 0.367*** (0.078)	- 0.552*** (0.104)	- 0.428*** (0.095)	- 0.938*** (0.144)
$\ln(C_D)$	0.113*** (0.031)	0.163*** (0.056)	0.139*** (0.039)	0.347*** (0.077)
Ind. controls	Yes	Yes	No	No
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.37	0.37	0.87	0.84
Observations	697,037	697,037	648	648

Notes: Each cell contains estimates from a separate regression. Only natives individual are considered. Dependent variable is indicated in the first column. All regressions use the basic definitions of both communicative and manual indices. The explanatory variable is the share of immigrants in a province-year cell. Columns (1) and (2) refer to regressions with the dependent variable measured at individual level. Region and year fixed effects are included. In these specifications, the set of controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group; the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in the province-year cell of the individual; the province GDP level in 2014. Columns (3) and (4) refer to regressions with the dependent variable measured at province-year level (110 provinces in the period 2014-2016 and 106 provinces for the period 2017-2019, for a total of 648 observations). Region and year fixed effects are included. In these specifications, the set of controls includes: the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in a province-year cell and the province GDP level in 2014. Specifications (1) use OLS estimator and Specification (3) use WLS with weights given by the number of observations in each province-year cell. Specification (2) and (4) use 2SLS using the shift-share instrument computed with 2003 as base year. Standard errors are clustered at province level in all regressions. R^2 refers to regressions in the first row.

*, **, ***: coefficient significant at 10%, 5% and 1% level, respectively.

migrants induces natives to increase their supply of communicative skills by just 0.11 percent. Looking at Column (2), it can be seen that estimating the same coefficients with the 2SLS estimator doesn't change the sign and the significance of the results. All the coefficients, however, become sensibly larger, evidencing a possible downward bias in the OLS estimates. In particular, when IV estimator is used, a 1 percent increase in the share of immigrants is associated with a 0.72 percent increase in the natives' relative supply of communicative tasks. Again, δ^M is responsible for more than three quarters of the value of δ .

Column (3) and (4) are the counterparts of Column (1) and (2) where the dependent variable is the average individual relative task supply in a province-year cell (Equation 3.7). As before, estimates of γ both in Column (3) and Column (4) confirm the prediction of the theoretical model. OLS estimation suggests that a rise by 1 percent in the share of immigrants in a province

Table 4.2: Effects on aggregate task supply

Estimator	(1) OLS	(2) IV	(3) WLS	(4) IV
$\ln(\frac{C}{M})$	0.227** (0.105)	0.369*** (0.140)	0.161 (0.117)	0.677*** (0.174)
$\ln(M)$	- 0.217*** (0.080)	- 0.345*** (0.100)	- 0.175** (0.073)	- 0.555*** (0.117)
$\ln(C)$	0.010 (0.032)	0.024 (0.052)	- 0.014 (0.037)	0.122* (0.067)
Ind. controls	Yes	Yes	No	No
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.35	0.35	0.86	0.84
Observations	774,216	774,216	648	648

Notes: Each cell contains estimates from a separate regression. Both immigrants and natives observations are considered. Dependent variable is indicated in the first column. All regressions use the basic definitions of both communicative and manual indices. The explanatory variable is the share of immigrants in a province-year cell. Columns (1) and (2) refer to regressions with the dependent variable measured at individual level. Region and year fixed effects are included. In these specifications, the set of controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group; the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in the province-year cell of the individual; the province GDP level in 2014. Columns (3) and (4) refer to regressions with the dependent variable measured at province-year level (110 provinces in the period 2014-2016 and 106 provinces for the period 2017-2019, for a total of 648 observations). Region and year fixed effects are included. In these specifications, the set of controls includes: the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in a province-year cell and the province GDP level in 2014. Specifications (1) uses OLS estimator and specification (3) uses WLS with weights given by the number of observations in the province-year cell. Specification (2) and (4) use 2SLS using the shift-share instrument computed with 2003 as base year. Standard errors are clustered at province level in all regressions. R^2 refers to regressions in first row.

*, **, ***: coefficient significant at 10%, 5% and 1% level, respectively

induces a rise in the average individual relative supply of communicative tasks by natives by 0.57% (a coefficient slightly greater than that in Column 1), whereas 2SLS estimation implies a surprising increase by even 1.29 percent (an effect 80% greater than that estimated in Column 2). Again, the main driver of these increases is represented by a large drop in the average supply of manual tasks by natives.

4.2 Immigration and the total relative task supply

Table 4.2, instead, reports the estimations of Equation (3.4) and (3.8), which evaluate the impact of immigration on the total relative supply of communicative versus manual skills in the market ($\frac{C}{M}$). Unlike the regressions in the previous section, these specifications use both natives and immigrants observations, and not only the former. As before, I also analyze whether this effect

is greater for communicative or manual tasks by running separate regression with $\ln(C)$ and $\ln(M)$ as dependent variables.

Columns (1) and (2) corresponds to Equation (3.4) estimated using OLS and 2SLS, respectively. As can be seen, the estimates of δ^{TOT} are positive and statistically significant. In particular, a one percent increase in the share of immigrants is associated with a rise in the relative supply of communicative tasks by 0.22%, if the coefficient is estimated with OLS, or by 0.37%, if the coefficient is estimated with 2SLS. This increase is almost fully explained by a drop in the supply of manual tasks, whereas there is no statistically significant effect on the supply of communicative tasks, since the coefficients have become basically zero. As regards regressions corresponding to Equation (3.8) in Column (3) and (4) (those using province-year cells as units of observation), the results are to some extent discordant. OLS estimation reports a positive but not significant impact of immigration on the relative supply of communicative task in a local labor market, whereas 2SLS estimation confirms the results of the previous regressions, founding an even greater effect. However, these last regressions do not use my favorite specification, as I have explained in Section 3.3, so that I decide to focus my attention on Column (1) and (2).

The outcomes of these two specifications are indeed undoubtedly interesting. The theoretical model developed by Peri and Sparber (2009), in fact, forecasts a reduction in the market relative supply of communicative skills in response to an increase in the number of foreign workers. However, this is only a partial equilibrium, since the model does not allow native-born supply curve to move after this immigration-induced shock in the labor market, so that the unique possible reaction of natives is that caused by the variation in communicative-jobs compensation (represented by a movement along the supply curve). The fact that my specifications actually estimate an increase in the relative task supply at the market level, not only suggest that natives change their task supply for reasons others than wage (and then that their supply curve shifts rightwards), but also that their reaction to the increase in the share of immigrants is so large to compensate the relative increase in the supply of manual task imputable to the immigrants.

4.3 Heterogeneous effects

4.3.1 Low-skilled natives

As previously analyzed in Section 3.1, the vast majority of immigrants in Italy is low-skilled. Moreover, immigrants are used to suffer from “skill downgrading” (Dustmann et al., 2016),

Table 4.3: Effects on relative task supply of low-skilled natives

Estimator	(1) OLS	(2) 2SLS	(3) WLS	(4) 2SLS
$\ln(\frac{C_D}{M_D})$	0.580*** (0.106)	0.793*** (0.157)	0.616*** (0.101)	1.058*** (0.167)
$\ln(M_D)$	- 0.446*** (0.080)	- 0.608*** (0.110)	- 0.474*** (0.074)	- 0.794*** (0.111)
$\ln(C_D)$	0.134*** (0.035)	0.185*** (0.060)	0.141*** (0.036)	0.264*** (0.068)
Ind. controls	Yes	Yes	No	No
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.26	0.26	0.86	0.84
Observations	547,017	547,017	648	648

Notes: Each cell contains estimates from a separate regression. Only natives with no college degree are considered. Dependent variable is indicated in the first column. All regressions use the basic definitions of both communicative and manual indices. The explanatory variable is the share of immigrants in a province-year cell. Columns (1) and (2) refer to regressions with the dependent variable measured at individual level. Region and year fixed effects are included. In these specifications, the set of controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group; the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in the province-year cell of the individual; the province GDP level in 2014. Columns (3) and (4) refer to regressions with the dependent variable measured at province-year level (110 provinces in the period 2014-2016 and 106 provinces for the period 2017-2019, for a total of 648 observations). Region and year fixed effects are included. In these specifications, the set of controls includes: the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in a province-year cell and the province GDP level in 2014. Specifications (1) uses OLS estimator and specification (3) use WLS with weights given by the number of observations in the province-year cell. Specification (2) and (4) use 2SLS using the shift-share instrument computed with 2003 as base year. Standard errors are clustered at province level in all regressions. R^2 refers to regressions in the first row. *, **, ***: coefficient significant at 10%, 5% and 1% level, respectively

so that even if immigrants own a college degree (and then they can be considered high-skilled workers), they tend to be employed in low-skill jobs in the host country. In this context, it is reasonable to affirm that the natives most affected by the competition of immigrants in their local labor markets are the low-skilled ones.

To test this statement, I perform Equations (3.3), (3.5) and (3.6) using only low-skilled natives as sample. Table 4.3 reports the results of these regressions. First, it can be seen that the coefficients computed with this subsample confirm the results reached in Section 4.1: the estimations of δ remain always positive and statistically significant at the 1% percent confidence level; the 2SLS estimates are again bigger than the OLS estimates; and the drop in the natives' supply of manual tasks counts for more than three quarters of the rise in natives relative supply of communicative tasks.

Comparing the results of Table 4.1 and Table 4.3 it is easy to see that in specifications that use the relative task supply of the individual as dependent variable, the coefficients computed including only low-skilled natives are to some extent higher than those computed considering all natives as sample population. In particular, analyzing the 2SLS estimations, a 1% increase in the share of immigrants was associated with a 0.72 percent increase in the relative task supply when all natives were considered, whereas now the same coefficient is equal to 0.79 percent. Instead, focusing the attention on the other specifications (where the dependent variable is the average individual relative task supply in the province), the situation is quite different. The coefficient in Table 4.3 actually becomes lower than its counterpart in Table 4.1, 1.06% and 1.29%, respectively. However, since for the reasons explained in Section 3.3, my preferred specifications are those using the relative task supply measured at the individual level, I can conclude that the effect of immigrants on task specialization is slightly greater among low-skilled natives.

4.3.2 Young vs. old individuals

The analysis in Section 3.1 has also highlighted the fact that immigrants are not equally distributed among age cohorts. Consequently, it is reasonable to believe that, according to age, some individuals suffer the immigrants-induced competition more than others. In particular, data have shown that the great majority of foreigners (about 65%) has an age which is below 44 years old. For this reason, I divide my sample of natives using that particular age as discrimen and I perform the specification expressed in Equation (3.3) for both these subsamples.

The results of this analysis are reported in Table 4.4. The first insight is that the estimates of δ remain positive for both groups. However, the coefficient is clearly bigger for younger observations than for older ones: more precisely, considering 2SLS estimations, a one percent increase in the share of immigrants is associated with a 0.80% increase in the relative supply of communicative skills if the individual is younger than 45 years old, and with a 0.67% increase, if instead, the individual is older than that age. As already said, this result could be explained by the fact that immigrants in Italy are more similar in production to the former group than to the latter. But another factor could be also the great segmentation typical of the Italian labor market: in the last decades, in fact, many governments had incentivized the use of more flexible types of contract, which have created a sensible disparity in terms of employment protection and job stability between who already was in and who instead was going to enter the labor market. It follows that it is less costly for the younger cohorts to change their jobs and move towards more

Table 4.4: Effects on young vs. old individuals

	(1)	(2)	(3)	(4)
Estimator	OLS	IV	OLS	IV
Group	16 ≤ Age ≤ 44		45 ≤ Age ≤ 74	
$\ln(\frac{C_D}{M_D})$	0.545*** (0.103)	0.796*** (0.171)	0.413*** (0.117)	0.665*** (0.157)
$\ln(M_D)$	- 0.400*** (0.078)	- 0.624*** (0.123)	- 0.332*** (0.090)	- 0.506*** (0.114)
$\ln(C_D)$	0.145*** (0.031)	0.173*** (0.061)	0.081** (0.036)	0.159*** (0.061)
Ind. controls	Yes	Yes	Yes	Yes
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.35	0.35	0.39	0.39
Observations	309,458	309,458	387,579	387,579

Notes: Each cell contains estimates from a separate regression. Only natives individual are considered. Dependent variable is indicated in the first column. All regressions use the basic definitions of both communicative and manual indices. The explanatory variable is the share of immigrants in a province-year cell. Columns (1) and (2) consider only native individuals with age below 45 years old. Region and year fixed effects are included. In these specifications, the set of controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group (in the range 16-44 years old); the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in the province-year cell of the individual; the province GDP level in 2014. Columns (3) and (4) consider only native individual with an age above 44 years old. Region and year fixed effects are included. In these specifications, the set of controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group (in the range 45-74 years old); the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in a province-year cell and the province GDP level in 2014. Specifications (1) and Specification (3) use OLS estimator. Specification (2) and (4) use 2SLS using the shift-share instrument computed with 2003 as base year. Standard errors are clustered at province level in all regressions. R^2 refers to regressions in first row.

*, **, ***: coefficient significant at 10%, 5% and 1% level, respectively.

communicative-intensive occupations in response to an eventual detrimental effect due to the arrival of new workers from abroad.

4.3.3 Macroregions

As already seen in Section 3.1, immigrants are not equally distributed among Italian macroregions (North, Central and South Italy). Moreover, in Section 3.2.3, it has been also shown that Italian provinces are very different in terms of unemployment rate, GDP and sector composition of the economy, highlighting how this discrepancy is especially evident between the North-Central and the Southern parts of the country.

For these reasons, it may be interesting to perform my analysis also dividing my sample

Table 4.5: Effect on natives by macroregion

Estimator	(1)	(2)	(3)	(4)	(5)	(6)
Macroregion	North		Center		South	
$\ln(\frac{C_D}{M_D})$	0.563*** (0.123)	0.757*** (0.189)	0.713*** (0.118)	0.947*** (0.156)	0.211 (0.144)	-0.075 (0.320)
$\ln(M_D)$	-	-	-	-	-0.154	0.095
$\ln(C_D)$	0.398*** (0.094)	0.595*** (0.132)	0.532*** (0.088)	0.671*** (0.094)	0.057 (0.126)	0.020 (0.282)
Ind. controls	Yes	Yes	Yes	Yes	Yes	Yes
Province controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.36	0.36	0.35	0.35	0.40	0.40
Observations	393,037	393,037	148,360	148,360	155,610	155,610

Notes: Each cell contains estimates from a separate regression. Only natives individual are considered. Dependent variable is indicated in the first column. All regressions use the basic definitions of both communicative and manual indexes. The explanatory variable is the share of immigrants in a province-year cell. All specifications refer to regressions with the dependent variable measured at individual level. Region and year fixed effects are included. Individual controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group; province controls includes: the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in the province-year cell of the individual; the province GDP level in 2014. Specifications (1) and (2) consider only Northern regions (Valle d'Aosta, Piemonte, Liguria, Lombardia, Trentino Alto-Adige, Veneto, Friuli-Venezia-Giulia and Emilia-Romagna). Specifications (3) and (4) consider only Central regions (Marche, Toscana Umbria and Lazio). Specification (5) and (6) consider only Southern regions (Abruzzo, Molise, Campania, Basilicata, Puglia, Calabria, Sicilia and Sardegna). Specifications (1),(3) and (5) use OLS estimator. Specification (2),(4) and (6) use 2SLS using the shift-share instrument computed with 2003 as base year. Standard errors are clustered at province level in all regressions. R^2 refers to regressions in the first row.

*, **, ***: coefficient significant at 10%, 5% and 1% level, respectively.

following this specific geographical distinction. Table 4.5 reports the results of this investigation. As can be seen, regressions concerning North and Central Italy confirm the conclusions of my principal analysis. The effect of immigration on the relative supply of communication tasks by natives is still positive and the coefficients have a similar magnitude of those in Table 4.1. In particular, when the share of immigrant increase by 1%, natives rise their relative supply of communicative versus manual tasks by 0.76% and 0.95%, respectively in the North and the Center of the country. As far as South Italy is concerned, however, coefficients approaches zero (and in fact become even negative in the 2SLS specification) and the effect become no longer significant.

Table 4.6: Effect on natives task supply (using extended definitions)

Estimator	(1) OLS	(2) IV	(3) WLS	(4) IV
$\ln\left(\frac{C_D^{EXT}}{M_D^{EXT}}\right)$	0.291*** (0.068)	0.446*** (0.099)	0.352*** (0.085)	0.834*** (0.142)
$\ln\left(M_D^{EXT}\right)$	- 0.251*** (0.053)	- 0.379*** (0.072)	- 0.289*** (0.063)	- 0.621*** (0.090)
$\ln\left(C_D^{EXT}\right)$	0.040 (0.028)	0.067 (0.481)	0.062** (0.031)	0.213*** (0.065)
Ind. controls	Yes	Yes	No	No
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.39	0.39	0.87	0.84
Observations	697,037	697,037	648	648

Notes: Each cell contains estimates from a separate regression. Only natives individuals are considered. Dependent variable is indicated in the first column. All regressions use the extended definitions of both communicative and manual indices. The explanatory variable is the share of immigrants in a province-year cell. Columns (1) and (2) refer to regressions with the dependent variable measured at individual level. Region and year fixed effects are included. In these specifications, the set of controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group; the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in the province-year cell of the individual; the province GDP level in 2014. Columns (3) and (4) refer to regressions with the dependent variable measured at province-year level (110 provinces in the period 2014-2016 and 106 provinces for the period 2017-2019, for a total of 648 observations). Region and year fixed effects are included. In these specifications, the set of controls includes: the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in a province-year cell and the province GDP level in 2014. Specifications (1) use OLS estimator and specification (3) use WLS with weights given by the number of observations in the province-year cell. Specification (2) and (4) use 2SLS using the shift-share instrument computed with 2003 as base year. Standard errors are clustered at province level in all regressions. R^2 refers to regressions in first row. *, **, ***: coefficient significant at 10%, 5% and 1% level, respectively.

4.4 Robustness check

4.4.1 Extended definitions of manual and communicative indices

The choice of O*NET variables to include in the creation of the manual and communication indices is arbitrary and therefore my results could be affected by this fact. Following Peri and Sparber (2009), I create also two alternative definitions of these indices, which can be defined as “extended”: the extended definition of the manual-intensity index adds to the abilities related to dexterity, coordination and strength also those related to hearing, visual and general perception; the extended definition of the communicative-intensity index instead includes, as well as oral and written comprehension abilities, also cognitive, analytical and vocal-related ones (see Table A1 in the Appendix).

Table 4.7: Main effects excluding Romanian immigrants

Estimator	(1) OLS	(2) IV	(3) OLS	(4) IV
$\ln(\frac{C}{M})$	0.500*** (0.128)	0.813*** (0.173)	0.276*** (0.125)	0.478*** (0.156)
$\ln(M)$	- 0.388*** (0.090)	- 0.622*** (0.121)	- 0.262*** (0.090)	- 0.434*** (0.110)
$\ln(C)$	0.112*** (0.041)	0.191*** (0.064)	0.014 (0.038)	0.044 (0.059)
Ind. controls	Yes	Yes	Yes	Yes
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.37	0.37	0.35	0.35
Observations	697,037	697,037	774,216	774,216

Notes: Each cell contains estimates from a separate regression. Specifications (1) and (2) consider only native individuals, specifications (3) and (4) consider both immigrant and native individuals. Dependent variable is indicated in the first column. All regressions use the basic definitions of both communicative and manual indices. The explanatory variable is the share of immigrants in a province-year cell excluding the Romanian immigrants. Region and year fixed effects are included. In these specifications, the set of controls includes: a dummy for the sex of the individual, a dummy for each education level, a dummy for each decennial age group; the average wage, the population density, the unemployment rate, the share of workers employed in the industry sector and the share of workers employed in the services sector in the province-year cell of the individual; the province GDP level in 2014. Specifications (1) and (3) use OLS estimator. Specification (2) and (4) use 2SLS using the shift-share instrument computed with 2003 as base year and excluding Romanian immigrants. Standard errors are clustered at province level in all regressions. R^2 refers to regressions in first row.

*, **, ***: coefficient significant at 10%, 5% and 1% level, respectively

Table 4.6 reports the results of Equation (3.3) and (3.7) using these extended definitions for the dependent variables. As can be seen, my results are robust to the definition of the manual and communication-intensity indices. The estimation of δ , in fact, remain positive and statistically significant for all the specifications, even though the absolute values become lower (the coefficient in Column 1 passes from 0.48 to 0.291, while the coefficient in Column 2 from 0.751 to 0.446). In this case too, the main driver of this variation is the drop in the supply of manual tasks by natives, rather than an increase in the supply of communication tasks (and actually δ^C becomes not statistically different from zero in the specification using individuals as unit of observation).

4.4.2 Romanian immigrants

In Section 3.1, it has been pointed out that the high share of immigrants coming from Romania is explained by the fact that Romanian is a Romance language as Italian and then Romanians

have fewer difficulties in learning Italian with respect to other languages. This insight can have a relevant impact on my analysis since the effect I want to detect in this dissertation is based on the fundamental assumption that Italians own a comparative advantage in language proficiency compared to immigrants. In my opinion, it is quite unrealistic to think that Romanians can actually be comparable to natives in the knowledge of the language, however, it is better to check if and how the effect changes by excluding immigrants from this specific country of origin.

To do this, I recompute both the actual share of immigrants and the shift-share instrument in each province-year cell excluding the number of immigrants coming from Romania and I run again Equation (3.3) and (3.7) using both OLS and 2SLS estimators. Table 4.7 reports the results of this analysis. As regards the effect on natives relative task supply (Column 1 and 2 of the table), the coefficients remain positive and statistically significant. The absolute value becomes slightly greater (from 0.48 to 0.50 with OLS and from 0.72 to 0.81 with 2SLS), indicating that Romanian has a lower impact in triggering the change in natives' behaviour than other immigrants. As before, the increase in the relative supply of communicative tasks by natives is mainly due to a significant drop in their presence in manual-intensive jobs rather than an increase in the communicative-intensive one. The same conclusions can be made looking at Column (3) and (4) which instead consider the effect of immigration on the aggregate relative task supply at the market level. It can be seen that also in this case there is no significant change in the value of the coefficients, so that it follows that my results are robust to the language proficiency level of Romanian immigrants

4.4.3 Omitted variable bias

In Subsection 3.3.1 I have copied with the fact that province fixed effects absorbed all the variation in the share of immigrants by substituting them with region fixed effects and then controlling for a series of variables concerning time-invariant province characteristics. This process, even though not orthodox, should provide an acceptable approximation. However, for reasons of data availability (my period of analysis is very close to the present and then some economic statistics has not been published yet, as well as the fact that some province characteristics are unobservable or difficult to measure), it is impossible for me to control for all this kind of variables, so that my specifications may suffer of an omitted variable bias.

To check this hypothesis, I perform the Oster test developed by Oster (2019). This test exploits the fact that, under specific assumptions, the observable controls can be informative

Table 4.8: Oster test results

Equation	(1) (3.3)	(2) (3.7)	(3) (3.4)	(4) (3.8)
<i>a) First stage regressions</i>				
Dep. variable	f_{ijt}	f_{ijt}	f_{jt}	f_{jt}
Biased β	0.405	0.406	0.405	0.406
Unbiased β	0.810	0.811	0.822	0.822
R_{max}	1.000	1.000	1.000	1.000
<i>b) Reduced form regressions</i>				
Dep. variable	$\ln\left(\frac{C_D}{M_D}\right)_{ipt}$	$\ln\left(\frac{C}{M}\right)_{ipt}$	$\ln\left(\frac{C_D}{M_D}\right)_{pt}$	$\ln\left(\frac{C}{M}\right)_{pt}$
Biased β	0.289	0.150	0.520	0.275
Unbiased β	0.195	-0.023	0.616	0.401
R_{max}	0.480	0.453	1.000	1.000
<i>c) 2SLS estimates</i>				
Dep. variable	$\ln\left(\frac{C_D}{M_D}\right)_{ipt}$	$\ln\left(\frac{C}{M}\right)_{ipt}$	$\ln\left(\frac{C_D}{M_D}\right)_{pt}$	$\ln\left(\frac{C}{M}\right)_{pt}$
Biased β	0.715	0.369	1.285	0.677
Unbiased β	0.241	-0.028	0.749	0.487

Notes: Oster test is performed using the Stata command *psacalc* on the first-stage and reduced-form regressions. Column (1) and (3) consider only native individuals, while Column (2) and (4) consider both native and immigrants individuals. Column (1) and (2) refer to regressions with the dependent variable measured at the individual level. In these specifications the dummy for the gender, the dummies for each age group, the dummies for each educational level and the year fixed-effects are considered as variable not explicative about the unobserved controls. Column (3) and (4) refer to regressions with the dependent variable measured at the province-year level. In these specifications the dummy for the gender, the dummies for each age group, the dummies for each educational level and the year fixed-effects are considered as variable not explicative about the unobserved controls. 2SLS estimates are computed dividing the reduced-form coefficient by the first-stage coefficient

about if and how the coefficient of interest would change if unobservable controls were added to the regression. In particular, Oster (2019) shows that the omitted variable bias due to the absence of the unobservable controls can be computed as a function of the movements in the R^2 and in the value of the coefficient, induced by the introduction of the observable covariates.

Two fundamental assumptions should be made to make sure that the test works properly. The first one is about the relationship between the effects that observable and unobservable controls respectively have on the treatment variable. Since the controls I have included in my regressions are unarguably the most important variables which affect the share of immigrants in a local labor market (my variable of interest), I believe that it is quite unrealistic to think that unobservable controls have a greater impact than observable. As a consequence, I assume

that unobservable can be at most as important as observable (this is equal to setting a $\delta = 1$ following Oster's notation). The second assumption instead concerns the R-squared from the hypothetical regression of Y on X and both the unobservable and observable controls (R_{max}). In this case, Oster (2019) suggest that R_{max} should be set at $1.3\tilde{R}$, where \tilde{R} is the R-squared from the regression of Y on X and the observable controls.

Table 4.8 reports the coefficients of interest of first-stage and reduced-form regressions², as well as the 2SLS estimations, computed dividing the latter by the former, before ("biased β ") and after ("unbiased β ") the Oster test. Columns (1) and (2) refers to the regressions linked to Equation (3.3) and (3.4), and therefore use individuals as observational units, whereas Columns (3) and (4) to Equation (3.7) and (3.8), and therefore use province-year cells as observational units. In performing the test, I consider the dummy for the gender, those for the age group, those for the educational level and the year fixed effects as covariates not related to unobservable controls, so that the region fixed effects, the unemployment rate, the GDP level in 2014, the population density and the shares of workers in the industry and in the services sectors are the variables used to compute the bias.

As regards the first-stage regressions, after the Oster test all the coefficients increase, showing a bigger relationship between the real share of immigrants in a province-year cell and the share estimated using the shift-share instrument in Equation (3.9). More precisely, the coefficient has doubled, passing from about 0.405 to 0.810. Focusing on reduced-form regression instead, regressions using individuals as units of observation (Column 1 and 2) show an unbiased coefficient which is lower than before, while in the others the coefficient is greater. In particular, it is worth noting that in Column (2) the coefficient has become negative, indicating that the response of natives could not be great enough to compensate the increase in the relative supply of manual skills induced by immigration, with the overall effect of a reduction of the relative supply provision of communicative tasks at the market level. Anyway, the coefficient is very close to zero and it may be not statistically significant. As a result of these variations, all the 2SLS coefficients have become lower, because of the great increase in the first-stage regression coefficient.

²Results of reduced-form regression are reported in Appendix B.

Chapter 5

Conclusions

Labor market effects of immigration remains one of the most puzzling issues faced by economists. Basically all the theoretical models concerning this topic agree in asserting that a positive labor supply shock, caused by an inflow of workers from abroad in the labor market, has a negative effect on the main outcomes of the natives, especially for those presenting characteristics that are more similar to those of the immigrants. Empirical researches, however, have not found unambiguous evidence able to confirm such predictions yet. For this reason, a recent branch of the literature has started to consider the hypothesis that previous models could be based on too simple assumptions, one of these represented by the fact that immigrants and natives with the same educational level and work experience are completely identical in performing all the productive tasks. In this regard, it is instead reasonable to think that natives own a comparative advantage in communicative and language-intensive tasks, whereas immigrants own a comparative advantage in manual and physical tasks, and that the two groups of workers specialize accordingly. If this is the case, then the negative effects that immigration should induce in wages and employment opportunities of natives can be significantly lower.

This dissertation tries to find evidence for this assumption, by studying the Italian labor market. In particular, my empirical analysis used O*NET data to measure the task content of the occupations in the Istat Labor Force Survey for the period 2014-2019. My results support the aforementioned assumption. I find that a one percentage-point increase in the share of immigrants is associated with a strongly statistically significant 0.72 percent increase in the relative supply of communicative versus manual task by natives. This rise is explained for three quarters by a drop in the supply of manual tasks and just for the remaining part by an increase in the supply of communicative ones. This effect is slightly higher for young and low-skilled natives (those who suffer the most the competition of immigrants in Italy) and in the Center rather than in the North of the country, while it is not significant in the South. Comparing

my results with those of similar papers on the topic, my coefficient is twice as bigger as that estimated by Peri and Sparber (2009) in the United States between 1960 and 2000, but in line with that estimated by Amuedo-Dorantes and De La Rica (2011) in Spain between 2000 and 2008.

Another interesting finding of my analysis regards the effect on the aggregate relative supply. The theoretical model predicts that immigration should, at least in a first moment, decrease the relative supply of communicative skills in the economy, since immigrants have a comparative advantage in manual-intensive jobs. This reduction should induce a rise in the relative compensation of communicative-intensive occupations, the fact that should mostly trigger the previously estimated reaction by natives. In this respect, my study finds that a one percent increase in the share of immigrants is actually associated with a statistically significant 0.37% rise in the aggregate relative supply of communicative versus manual tasks. This result indicates that the reaction of natives is large enough to compensate for the initial reduction, suggesting that factors other than wage may be also determinant in the natives' choice of specializing in communicative-intensive occupations.

However, because of very scant data availability, for my analysis I have been forced to use a specification which is not my "first-best". In this regards, I checked whether the impossibility to introduce all the controls has generated an omitted variable bias by performing the Oster test, finding that in my main specifications an upward bias actually exists. More precisely, the predicted "unbiased" coefficients imply that a 1 percent increase in the share of immigrants in a local labor market is associated with a 0.24 and -0.03 percent variation in the relative supply of communicative tasks by natives and at the market level, respectively. The second coefficient is, though marginally, in contrast with the positive effect previously detected, indicating that the earlier result is not robust to the inclusion of possible omitted variable. As a consequence, I cannot exclude that the impact of immigration on the aggregate relative supply could actually be zero.

Overall, my findings have some relevant policy implications. In the first place, the fact that natives react to an increase in the share of foreign-born workers by specializing in occupations in which immigrants cannot compete corroborates the results of those papers that find small or negligible impact of immigration on the wages and employment opportunities of Italians. Confirming that immigration does not negatively affect labor market outcomes of Italian natives is a crucial point for a country which may be forced to rely on large inflows of workers from abroad to deal with the inevitable issues concerning the sustainability of its welfare system, caused by the population aging. In the second place, these results also suggest that immigration, inducing

natives towards task specialization and occupational upgrading, is able to raise job mobility, enhancing the job matching efficiency and in general the overall productivity of the economy. This is particularly important in a country like Italy, characterized by a large proportion of open-ended contracts and high Employment Protection Legislation levels.

Appendix A

Indices definitions

Table A.1: Definitions of task-intensity indices

Type of skill	Definition	Skill sub-type	O*NET Variables
Manual (or physical) skills	Basic definition: movement and strength	Limb, hand and finger dexterity	Arm-hand steadiness, manual dexterity, finger dexterity, control precision, multilimb coordination, response orientation, rate control, reaction time, wrist-finger speed, speed of limb movement
		Body coordination and flexibility	Extent flexibility, dynamic flexibility, gross body coordination, gross body equilibrium
		Strength	Static strength, explosive strength, dynamic strength, trunk strength, stamina
Communication (or language) skills	Extended definition: movement and strength plus sensory- perception skills	General perception	Perceptual speed, spatial orientation, visualization, selective attention, time sharing
		Visual perception	Near vision, far vision, visual color discrimination, night vision, peripheral vision, depth perception, glare sensitivity
		Hearing perception	Hearing sensitivity, auditory attention, sound localization
Communication (or language) skills	Basic definition: oral and written	Oral	Oral comprehension, oral expression
		Written	Written comprehension, written expression
		Cognitive and analytical	Fluency of ideas, originality, problem sensitivity, category flexibility, mathematical reasoning, number facility, deductive reasoning, inductive reasoning, information ordering, memorization, speed of closure, flexibility of closure
	Extended definition: oral and written plus cognitive, analytical and vocal skills	Vocal	Speech recognition, speech clarity

Notes: O*NET variables are from the O*Net ability survey available at <https://www.onetcenter.org/database.html>. The definitions of the different indices follow those used by Peri and Sparber (2009)

Appendix B

Reduced-form regressions

Table B.1: Reduced-form regressions

	(1)	(2)	(3)	(4)
	$\ln\left(\frac{C_D}{M_D}\right)_{ipt}$	$\ln\left(\frac{C}{M}\right)_{ipt}$	$\ln\left(\frac{C_D}{M_D}\right)_{pt}$	$\ln\left(\frac{C}{M}\right)_{pt}$
\tilde{f}_{jt}	0.289*** (0.073)	0.150** (0.065)	0.520*** (0.072)	0.275*** (0.054)
Ind. controls	Yes	Yes	No	No
Province controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	697,037	774,216	648	648
R^2	0.370	0.349	0.89	0.873

Notes: Dependent variables in the first row. The explanatory variable is the shift-share instrument computed with 2003 as base year. Specification (1) and (2) use individuals as observational data. The dependent variables in these specification are the relative supply of communicative tasks by natives and at the market level, respectively. Specification (3) and (4) use province-year cells as observational units. In these specifications, the dependent variables are the relative supply of communicative tasks by natives and at the market level, respectively and the coefficients are computed with WLS, using the number of observations in each province-year cell as weights. Specification (1) and (3) includes only native individuals, whereas specification (2) and (4) includes both native and foreign-born individuals. Individual controls include a dummy for the sex of the individual, a dummy for each decennial age group and a dummy for each education level. Province controls include the unemployment rate, the population density, the Gdp in 2014, the mean wage, the share of workers employed in the industry sector and the share of workers employed in the services sector in each province-year cell. Region and year fixed effects are included in all specifications. Clustered standard errors are reported in parenthesis.

*, **, ***: coefficient significant at 10%, 5% and 1% level, respectively.

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