Three essays in labor economics

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Ai pellegrini d'Oriente, a Roberto e alla mia famiglia

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Introduction

Developed societies are undergoing profound changes. The decrease in childbirths observed in almost all developed economies is leading to a rapid aging of population. This poses several challenges to their labor markets, since the burden of informal elderly care on active labor force is constantly increasing over time and threatens economic development in the long run. Migratory flows from developing countries can partly revert these trends. Nevertheless, new migration waves can raise readjustment problems to the receiving labor markets and can be opposed by the incumbent population.

In this thesis, I investigate some aspects of the two main challenges faced by developed societies: aging and migration. In the first chapter, I consider the cultural determinants of elderly care arrangement decisions. From a policy point of view, understanding the determinants of such decisions can help tuning elderly care services to the needs of the elderly, relieving the elderly care burden of informal care givers, i.e. working age family members. In the second and third chapter, instead, I consider some aspects of the impact of migration on the labor market. Particularly, in the second chapter I investigate the role of language abilities in determining the substitutability between native and foreign workers. In the third chapter, I consider the role of product market conditions on the employment of migrant workers. Both aspects are crucial to design migration policies able to limit the displacement effect of migrant workers on native workers and to foster the economic potential of the economy.

Also, in the three chapters I consider different economic contexts and implement different empirical strategies. The first two chapters exploit the cultural diversity of Switzerland to infer their conclusions on elderly care arrangements and migrant-native substitutability. The third chapter, instead, exploits a structural change in international trade patterns and focuses on the United States.

The empirical strategy of the first chapter *"The role of culture in long-term care arrangement decisions"* (with Giuliano Masiero and Fabrizio Mazzonna) is based on Swiss data and consists in a spatial regression discontinuity at the linguistic border between French and German speaking municipalities of bilingual cantons. In this way, we compare the decisions of people belonging to different cultural groups to enter a nursing home. German speaking elder individuals usually enter the nursing homes in better health conditions with respect to their French speaking counterparts and this result is likely to be due to differences in the strength of family values. This suggests that people with a different cultural background may give different behavioral responses to the same public intervention. Thus, the policy maker should be aware of such differences to correctly target policy interventions in the elderly care market.

The second and the third chapters investigate the issue of migration and both advise the policy makers on different aspects that migration policies should account for. The second paper, *"What drives the substitutability between foreign and native workers? Evidence about the role of language"* (with Fabrizio Mazzonna), studies the role of language in driving the substitutability between native and foreign workers. In other words, it checks whether workers sharing the linguistic background of native workers are better substitutes for native workers than foreign workers with a different linguistic background. To this aim, I modify the model developed by Ottaviano and Peri (2012) and estimate some structural parameters, comparing workers of different nationalities and different linguistic backgrounds. The results show that migrant workers with the same linguistic background of native workers do not specialize in different occupations and are potentially perfect substitutes for native workers. By contrast, migrant workers with a different linguistic background (but also native workers with a different linguistic background) tend to specialize in more manual intensive tasks and are somewhat complementary to resident natives.

Finally, in the third paper, *"The role of Chinese import competition on the employment of migrant workers"*, I try to understand whether the firms play an active role in demanding migrant labor. In particular, I analyze the role of product market competition in determining the employment of migrant workers. To this aim, I follow the empirical strategy of Autor et al. (2013) and exploit the upsurge of China as a world leading manufacturing exporter to evaluate the effects of greater product market competition on the employment of migrant workers in the manufacturing sector. However, since Chinese import exposure can be correlated with manufacturing employment, I instrument import penetration from China to the US with import penetration from China to other high income countries. The empirical results show that an increase in import competition is positively related to the employment of foreign workers. This seems to be related to the greater productivity of foreign workers. Thus, firms facing an increase in competition in the final good market may prefer to retain more productive migrant workers. This could worsen the displacement of native workers induced by a negative event in the final product market, raising anti-immigration feelings among native population.

Chapter 1

The role of culture in long-term care arrangement decisions

1.1 Introduction

Population aging and the change in the family structure are expected to increase long-term care (LTC) expenditure substantially in the next 50 years, raising the burden on society to cover elderly care services. In 2010, public LTC expenditure accounted, on average, for 1.8% of GDP across the EU-27 and this expenditure is expected to double by 2060 (Oliveira Martins and de la Maisonneuve, 2013). However, the LTC market is still considered too small if we take into account the high expenditure associated with the old age dependency risk (Brown and Finkelstein, 2007). A quite voluminous literature (see Norton, 2016 for a review) has investigated the LTC insurance puzzle focusing on several supply side (e.g., imperfect competition and asymmetric information) and demand side (e.g., limited rationality, biased risk perception and informal care) factors. More recently, attention has been also devoted to the role of cultural factors,[1] mainly to explain the large cross-country variation in the size of this market (Costa-Font, 2010). This paper shows how and to what extent cultural factors may influence the LTC market. To this aim we compare LTC arrangement decisions across language regions in Switzerland using a spatial regression discontinuity design (RDD).

LTC arrangements can be distinguished between residential care provided in nursing homes and home-based care provided at the individual's home. While residential care is always formally provided, home-based care can be either formal or informal - that is, provided by family members. Generally speaking, LTC arrangements respond to different needs and the choice among them is the

[1]Following the growing literature on the economic effects of culture (e.g., Alesina and Giuliano, 2015), we refer to culture as customary beliefs, attitudes and system of social norms that characterize a particular group and that are transmitted from generation to generation.

result of different factors. The health condition of the older person is of fundamental importance in deciding the amount of formal and informal care required (Bonsang, 2009; Norton, 2000). In many cases, elderly people choose residential care only when their health condition is too critical to be cared at home (Ryan and Scullion, 2000). Another important determinant is the availability of substitutes for care. Indeed, cohabiting with other people increases the probability of receiving informal care, while living alone is significantly associated with higher formal home-based care and nursing home use (Kemper, 1992). Finally, payment schemes for formal health care services are also found to influence LTC use (e.g., Siciliani, 2013; Orsini, 2010).

Social scientists have also explored the cultural-driven north-south gradient in LTC arrangements across European countries. The elderly are more likely to be instituzionalized (i.e. in nursing homes), and more likely to use formal health care services in Continental and Scandinavian countries than in Mediterranean countries (e.g., Bolin et al., 2008). Costa-Font (2010) offers a cultural explanation for this phenomenon and, more generally, for the limited development of the LTC insurance market in many countries. He finds that family ties appear to influence the decisions to purchase LTC insurance, and that European countries with stronger family ties exhibit lower levels of formal LTC coverage. This is consistent with the sociologists' view according to which "weak" and "strong" family ties countries show very different cultural norms about the role of the family in taking care of the elderly (Reher, 1998). Nevertheless, in these studies the presence of significant differences among Southern, Central and Northern European countries in LTC utilization might be driven by the large differences in institutional settings. Indeed, economic conditions, institutional factors and cultural norms are very difficult, if not impossible, to disentangle using cross-country studies.

We overcome this problem by exploiting the unique institutional setting provided by Switzerland. Switzerland is a confederation of 26 states called cantons, and counts four distinct cultural groups corresponding to four different languages spoken, namely German, French, Italian and Romansh. These language groups are geographically well-delimited, and the discontinuity in the probability of speaking a given language is quite sharp at language borders. Moreover, there are large differences between cultural groups, particularly between German speaking communities and communities speaking a language of Latin origin (French, Italian and Romansh).

Eugster et al. (2011) show how the large cultural difference between these two broad language groups shapes the demand for social insurance. In particular, the support of redistribution policies and for the expansion of the social insurances is larger among Latin-speaking Swiss residents compared with their German-neighbors in adjacent municipalities. Moreover, the authors show the presence of stronger family ties among Swiss-Latin individuals. Using Swiss data from the European Value Survey (EVS) and the International Social Survey Program (ISSP), we also document the presence of clear differences between Latin and German speaking people living in Switzerland for some selected questions about family value and elderly care. Figure 1.1 clearly shows that Latin speaking respondents are more likely to consider the family as very important in their life. They also believe that elderly care should be provided by family members (especially adult children), and spend a larger amount of time in providing care for family members than people living in German areas.

In this paper, we argue that the before described difference in family values across the two main Swiss cultural groups - German and Latin - gives rise to large differences in the demand for LTC arrangements. First, we use a simple theoretical framework to predict how different individual preferences may affect the dependency level at entry (i.e., health conditions) in nursing homes and, as a consequence, the relative provision of home-based care compared to nursing homes. In particular, if stronger family ties imply stronger preferences for care at home, Latin speaking individuals are expected to enter a nursing home in worse health conditions and use more formal home-based care with respect to German speaking individuals. Then, using Swiss administrative data on nursing homes and formal home-based care providers, we provide empirical evidence that supports our theoretical predictions.

While cantons have large power in many economic sectors, including the organization of LTC services, linguistic borders do not always coincide with cantonal administrative borders. Particularly, there are three French and German speaking bilingual cantons and one Italian, Romansh and German speaking trilingual canton (see Figure 1.2). As in Eugster et al. (2011), we disentangle the effect of culture from the effect of different institutional settings using a spatial RDD at the linguistic border between German and French speaking municipalities in the three bilingual cantons. Thus, contrasting LTC choices of people living on different sides of the linguistic border within the same canton (i.e., holding supply and institutional factors constant), we can identify the impact of culture on LTC arrangement decisions. We do not use the variation coming from the trilingual canton (Graubünden) because the identification would be based on too few municipalities and potentially confounded by important geographical discontinuities (i.e. the Alps).

Our results are robust to a large battery of robustness checks. We show that there are no discontinuities in our covariates and institutional characteristics that might potentially confound our analysis, such as socio-demographics characteristics, income, home ownership, prevalence of several (aging related) diseases, mortality and several supply side characteristics. Our results are also robust to the bandwidth choice and to different parametric and non-parametric specifications.

To provide further evidence that our results are driven by cultural differences in family values, we also investigate the mechanisms behind our results. Many alternative explanations are rejected when testing the continuity assumption. Then, we use survey data to investigate several household characteristics that are known to affect LTC choices. Again, we do not find evidence of differences in household composition and size across linguistic groups. We do instead find evidence of a larger presence of informal care from household members and relatives in Latin speaking regions, a result that supports the family ties explanation.

This paper provides a new contribution to the literature about the determinants of LTC use, showing the importance of culture on LTC arrangement decisions. The role of culture in shaping economic outcomes has been widely debated in the literature (e.g., Alesina and Giuliano, 2015; Carroll et al., 1994; Fernandez and Fogli, 2009; Giuliano, 2007). For instance, Giuliano (2007) investigates how culture affects living arrangements, showing that children of Southern European immigrants in the United States tend to cohabit with their parents up to older ages as compared to children of Northern European immigrants. Indeed, our evidence allows to shed some light on one of the driving forces behind the substitutability between different LTC arrangements.

The remainder of the paper is structured as follows. The next section explains the institutional background and provides some basic insights about the organization and the distribution of formal LTC in Switzerland. Section 1.3 provides a simple theoretical framework to understand the role of culture in shaping LTC arrangement decisions, while Section 1.4 presents the data. The empirical strategy is presented in Section 1.5 while Section 1.6 presents the results. Finally, Section 1.7 concludes.

1.2 Institutional and cultural background

Language, culture and administrative borders

In Switzerland there are 26 cantons and 4 official languages: German, French, Italian and Romansh. In 2013, the Swiss population amounted to about 8 million people. German was spoken by 63.5% of the population, French by 22.5%, Italian by 8.1% and Romansh only by 0.5%. Linguistic areas are well-delimited on the territory: the German speaking part is located in the Centre-East of the country, French is spoken in the West, Italian in the South and Romansh in some valleys of the South-East.

However, linguistic areas do not always coincide with cantonal administrative borders. Specifically, three cantons — Berne, Fribourg and Valais —overlap with both French and German speaking areas, while the canton of Graubünden overlaps with German, Italian and Romansh speaking areas (see Figure 1.2). The language discontinuity in the Graubünden canton is limited to some specific valleys. On the contrary, the language discontinuity between French speaking areas in the Western part of the country and German speaking areas in the Central part runs from North to South without geographical barriers separating the two linguistic areas. The mountain barrier of the Alps is located in the South, and runs from East to West, while the Northern part is mainly covered by hills. Thus, there are no morphological differences between the two sides of this linguistic border. The linguistic border has historical roots and can be considered as fairly exogenous. As discussed by Eugster et al. (2011, 2016) it traces back to the Roman time (around VI-VII century A.D.) while cantonal boundaries emerged only during the late Middle Ages.

It is also worth noting that the linguistic border does not coincide with a religious border. However, Swiss-Latin border towns are characterised by roughly 14 percentage points fewer Protestants as compared to Swiss-German border towns. This percentage is compensated by a corresponding higher share of Catholics (Eugster et al., 2011) with large heterogeneity across municipalities. Even though cultural norms might be shaped by religion membership, this does not appear to be an explanation for the the large difference in family values and LTC arrangements across the two linguistic groups. In particular, all the results reported in this paper are robust to the inclusion of controls for religion (Table 1.A.4).

Our analysis involves 4 administrative levels: the Confederation, cantons, districts and municipalities. The Confederation sets general guidelines, Cantons are the states of the Swiss Confederation with large autonomy in terms of healthcare organization and policy, while districts are aggregations of municipalities within a canton. Districts do not have any legislative or executive power, nor any democratically elected authority. Still they play a role in the organization of some services, such as home-based care. Finally, municipalities are entitled to organize and guarantee the provision of LTC on their territory. To this end, they can coordinate with other municipalities or with the canton.

LTC organization

The Swiss health care system is based on private health care insurance, which is compulsory for all citizens. The LTC delivery system is highly decentralized and cantons started a federal coordination only recently. The Confederation only sets the general guidelines, such as the maximum contribution of patients and health insurers to both residential care and home-based care. Cantons are in charge of the organization of LTC services and guarantee health insurance subscription to those who cannot afford it.[2] Within the guidelines imposed by the Confederation, each canton may set different contributions for patients and health insurers. In particular, German speaking

[2]Notice that more than 50% of patients in nursing homes receive subsidies from local governments.

regions have so far relied more heavily on nursing homes, whereas French and Italian speaking areas have developed more home care services. According to the last change in the federal law on LTC provision,[3] about 65% of the cost of health care provided by either nursing homes or home-based health care services is covered by compulsory health insurance, and their reimbursement is regulated by the federal law on the compulsory health insurance.[4] Patients or residents themselves can be made to cover up to 20% of such costs (a ceiling of approximately 8,000 CHF per year). The remainder is covered by public authorities (cantons and municipalities). However, the canton establishes whether the residual costs for LTC are covered by the canton itself or by the patient's municipality of residence. Conversely, residential costs and help at home for activities of daily living (ADL) and instrumental activities of daily living (IADL) are generally covered by the patients through out-of-pocket expenditures (that might depend on income or wealth) or supplementary LTC insurances. However, cantons might decide to provide subsidies to cover at least partially the residual out-of-pocket expenditure.

1.3 Theoretical framework

Several theoretical models provide guidance for optimal LTC arrangement policies (e.g., Jousten et al., 2005; Kuhn and Nuscheler, 2011), but none of them explicitly considers the role of culture in shaping LTC arrangement decisions. In this section we provide a simple theoretical framework to investigate the impact of culture on two outcomes: the dependency level at entry in nursing homes and, as a consequence, the relative provision of home-based care with respect to nursing home care. Although a discussion about the amount of informal care received from relatives is beyond the scope of this paper, this framework can be easily extended to encompass informal care provision. Further details are provided in the footnotes.

Consider the following quasi-linear utility function:

$$U(C, LTC) = C + d\phi(LTC) \qquad d \in [0,1] \tag{1.1}$$

where C is consumption, ϕ is an increasing and strictly concave function of LTC, and d is the intensity of care required by the elderly person, i.e. the dependency level. Equation (1.1) can be interpreted as either the household utility or the elderly person's utility, depending on the subject making LTC choices. LTC can be measured in day units or in multiple-day units. Besides, if the elderly person is in good health, i.e. $d = 0$, the household does not spend any amount of income in LTC services.

[3] The federal law was approved in June 13, 2008 and came into force in 2011.

[4] SR 832.10 - Federal law dated March, 18th 1994.

LTC services can be further subdivided into home-based care (HB) and nursing home care (NH):

$$LTC = \delta HB + (1-\delta)NH, \qquad \delta \in [0,1] \tag{1.2}$$

where δ is the preference parameter for home-based care, which captures the influence of culture. Indeed, individuals with stronger family ties are expected to show a higher value of δ with respect to individuals with weaker family ties. Home-based care and nursing home care are assumed to be perfect substitutes, since elderly people entering a nursing home do not receive any home-based care, and vice-versa.[5]

Assuming that the price of consumption is the numeraire, the budget constraint is

$$C + p_h(d)HB + p_n NH = \omega, \qquad p_h'(d) > 0 \tag{1.3}$$

where $p_h(d)$ is the price of home-based care, which is an increasing function of the dependency level, d. p_n is the price of nursing homes, and ω is the endowment of the household. If HB and NH are expressed in days of care, $p_h(d)$ can be interpreted as the price of one day of home-based care, which becomes progressively more expensive as the elderly's health condition deteriorates. In other words, worse health conditions may require more hours of care, increasing the daily cost of home-based care.[6] For simplicity, we assume p_n to be independent of the elderly's health condition, since fixed costs in a nursing home usually outweigh variable costs due to adverse health conditions.[7]

The Swiss LTC organization fits well this framework. Generally, the price paid for nursing home care does not vary with the intensity of care required by the elderly person and is based on a daily tariff. Conversely, home-based care is provided in hours. Therefore, the more adverse the health conditions of the patient, the larger the number of daily hours of home-based care required, and the higher the daily price of home-based care. As a result, it seems reasonable to assume that for low levels of dependency the price of one day in home-based care is lower than the price of one day in nursing homes, while for high levels of dependency home-based care is more expensive than nursing home care.

[5]Notice that this framework can be easily expanded to encompass the distinction between formal and informal care provision. Indeed, the home-based care variable HB can be further decomposed as $HB = [\theta IF^\rho + (1-\theta)FM^\rho]^{\frac{1}{\rho}}$, where IF is the amount of informal care, FM is the amount of formal home-based care, θ is a preference parameter for informal care and ρ is the elasticity of substitution between the two. This framework allows for imperfect substitutability between formal and informal home-based care. Nevertheless, a thorough investigation of the interaction between formal and informal care is beyond the scope of this paper.

[6]In the case of formal home-based care this cost is monetary, while in the case of informal care this cost can be measured as the monetary value of the time spent by the caregiver.

[7]To relax this assumption, let the nursing home price depend on the severity of the elderly's health status. Since fixed costs play a greater role in nursing homes than in home-based care, daily home-based care prices increase more rapidly with the severity of the elderly's health condition than daily nursing home prices, i.e. $p_h'(d) > p_n'(d)$.

The effect of culture on LTC choices

Using Equations (1.1)–(1.3), we can see that households are indifferent between nursing homes and home-based care if

$$\delta p_n = (1 - \delta) p_h(d). \tag{1.4}$$

In words, the elderly person enters a nursing home if the left-hand side of the equation is smaller than the right-hand side, that is when the weighted price of one day in nursing home care is smaller than the weighted price of one day in home-based care. Prices are weighted by preferences for home-based care. Indeed, the higher the preference for home-based care, the smaller the nursing home price to induce entrance in a nursing home. Therefore, the threshold dependency level beyond which the elderly person enters the nursing home can be obtained from Equation (1.4) as

$$d^* = p_h^{-1}\left(\frac{\delta}{1-\delta} p_n\right). \tag{1.5}$$

Notice that the inverse of a strictly increasing function is still an increasing function, and therefore the dependency level at entry is positively related to the preference parameter for staying at home. This means that the threshold dependency level above which the elderly person is willing to enter a nursing home is higher for individuals with strong family ties (and thus high preference parameter for home-based care) than individuals with low family ties (small δ). Figure 1.3 shows graphically the results using a simple functional form for $p_h(d)$. For combinations of d and δ above the curve, the elderly person enters a nursing home, while for combinations of d and δ below the curve, the elderly person receives home-based care. In the empirical part of the paper, we are going to test the validity of this relationship.

Note that the household decision can be decomposed in two parts: first, the decision whether to purchase home-based or nursing home care, and second, the decision about the quantity of the chosen type of care to purchase. If we focus only on the second part of the problem, the quantity of service to buy, we can see that for positive values of the dependency level d the utility function is strictly concave. This means that preferences in the amount of service to purchase are single-peaked. Thus, assuming that individual preferences are aggregated according to a majoritarian voting rule, and that households correctly reveal their preferences, the median voter theorem applies and the optimal per capita provision of care corresponds to the preferences of the median-ranked household. From a supply viewpoint this implies that, if the government (or the market) aggregates citizens' preferences for home-based care, the higher the average δ in the population the higher the provision of home-based care, *ceteris paribus.*

To sum up, from this simple theoretical framework we obtain two preliminary results: (a) the dependency level at entry in nursing homes is higher for people with stronger preference for home-based care, and (*b*) if people are allowed to freely choose their preferred LTC arrangement option, LTC provision should reflect population preferences.

In the remaining of this paper, we exploit the within canton variation in the language spoken to show that Latin and German speaking areas are characterized by quite different social values and preferences, which give rise to remarkable differences in the demand for different LTC services. However, if result (*b*) applies, differences in the supply of LTC services across cantons should also reflect, at least partially, cultural differences across cantons. As a consequence, our identification strategy —that exploits only the cultural variation within cantons— should only capture a lower bound of the total effect of culture on LTC markets.

1.4 Data and descriptive statistics

1.4.1 Data

The main data source is the statistics on socio-medical institutions (SOMED) available from the Swiss Federal Statistical Office. SOMED is an administrative dataset containing data from nursing homes between 2006 and 2013. Each nursing home is required to transmit information about its clients, costs, revenues and personnel employed. Data about health care provision to clients are detailed and include length of stay, intensity of care received, type of arrangement within the nursing home, provenience and destination of the elderly. From 2007 on, a personal number is assigned to each client, allowing for consistent tracking of individuals over time. Given the nature of this dataset, there is limited information about socio-demographic characteristics of clients. However, for each individual we observe the place of residence before entering the nursing home, age, and gender.

Dependency level at entry

Following the insight of our theoretical model, the main dependent variable of interest is the dependency level at entry, which we define as the intensity of initial care received by the patient. To measure the dependency level, we use a harmonized scale that ranges from 0 to 4. During the period of interest (2007-2013), the measurement instruments adopted for reporting the intensity of care in nursing homes were not uniform across cantons. Nevertheless, given that each instrument can be converted into minutes of care provided, it was possible to harmonize the dependency levels and to collapse them into one major scale ranging from 0 to 4. In particular, each point of the scale corresponds to one additional hour of care per day. It is worth noting that the measurement instrument does not change at the linguistic border in the three bilingual cantons. We restrict the analysis of the dependency level at entry to people aged 50+ entering a nursing home with the intent to stay for a long time. Moreover, we focus on the dependency level "at entry" to avoid the confounding factor of nursing home treatment. More details regarding the construction of the dependency level at entry are provided in Appendix 1.A.1.

We also consider two other proxies of the dependency level: age at entry and place of residence before entering the nursing home. The idea behind using age at entry is that the older an individual, the higher the likelihood of physical and mental impairments. However, we expect age to be a more noisy indicator of frailty with respect to the dependency level, because life events and health behaviors adopted during the whole life-cycle may affect individual's health at older ages. For instance, if people that would have entered at older ages in nursing homes show worse health-related behaviours, they may enter a nursing home at younger age, because their health status deteriorates faster than people with better health-related behaviour. Indeed, while Latin-speaking communities might be more reluctant to enter a nursing home compared to their German speaking counterparts, they also show worse health-related behaviours (Abel et al., 2013).

Also, the place of residence before entry is an interesting indicator of individual preferences towards LTC arrangements. In areas with greater preference for staying at home, the entrance in nursing home is postponed until the health conditions of the elderly person are too problematic to be cared at home. Thus, in these areas we expect more people entering a nursing home from hospital or from other rehabilitative institutions. On the contrary, where people decide to enter a nursing home in relatively healthier conditions, we expect more people to enter from home. The results based on age at entry and place of residence are very similar to those reported in the main text using the dependency level (see Appendix for further details).

Auxiliary data

We use additional datasets to explain why people in Latin speaking areas enters a nursing home in worse health conditions. First, we exploit the home care survey (HCS) which collects administrative data from home-based care providers. The time span of this database is from 2007 to 2013. Data about clients are aggregated by provider, and therefore it is not possible to make any inference about the intensity of care received by each person. The only available information is the number of clients receiving care, hours provided, and the number of cases by type of care, and (for some types of care) age group. Since home-base providers usually take care of clients residing in different municipalities (to exploit economies of scale from service provision, especially in rural environments) we aggregate the information at district level.

Second, we use voting data from national referenda. Switzerland has a long-standing tradition of direct democracy and many referenda take place every year. In the main text, we use data from the 2013 referendum on family policies about the approval of an amendment to the Swiss Constitution promoting the reconciliation between work and family duties and considering the needs of families in government policies. Specifically we use the share of people voting yes in each municipalities. Eugster et al. (2011) show that there are sharp differences in referendum outcomes on social issues between French and German speaking municipalities in bilingual cantons. These differences can be attributed to cultural differences between the two linguistic areas. As a result, referendum outcomes should be a reasonable proxy for preferences in this context. Other referenda involving the family (e.g., a referendum in 1996 on the introduction of the maternity leave) lead to similar conclusions.

Third, we use survey data providing information on household characteristics and informal care. In particular, we exploit the 2000 Public use sample (PUS) of the Swiss census (a random drawn sample of 5% of the population) to obtain additional information on household characteristics in the three bilingual cantons, and the fourth wave (2010) of the Survey of Health Ageing and Retirement in Europe (SHARE) for information on the level of informal care. All the other control variables at municipal and hospital level are obtain from the Swiss Federal Statistical Office (FSO) and are described in the Appendix 1.A.2.

1.4.2 Descriptive statistics

In Table 1.1, we report basic descriptive statistics at individual level by linguistic area in the three bilingual French- and German speaking cantons. The variables of interest are *Dependency level at entry*, *Age at entry*, *Residing at home* and *Gender*. On average, French speaking individuals show higher dependency level at entry, age at entry, and are less likely to be at home prior to institutionalization. However, a mean comparison test cannot reject the null of equal means for *Age at entry* and *Gender*.[8]

Graphical evidence at district level for the whole country seems to indicate that people in Latin regions (and particularly in the French speaking area) enter nursing homes in worse health conditions, and use formal home care more often than people living in German regions (Figure 1.4).[9] One could argue that this pattern may be driven by average worse health conditions of people living in Latin speaking areas. As a robustness check, we use the share of people over 65 in nursing homes instead of the dependency rate and obtain very similar results (Figure 1.A.1). Such evidence suggests that people in Latin speaking regions enter the nursing home in worse health conditions because they postpone their entrance, rather than being in worse health conditions

[8]The standard errors in these tests are robust and clustered at municipal level.

[9]We use this level of aggregation to compare nursing home data with formal home-based care data. As discussed in Section 1.4, home-based care data are only at provider level.

compared to people in German speaking regions. This is also confirmed by Figure 1.A.2 where we show that there are no discontinuities in common diseases among the elderly at the language border in the three bilingual cantons (see Section 1.6.1 for further details). If ever, mortality rate is slightly smaller on the Latin side (Figure 1.A.3).

1.5 Empirical strategy

To causally identify the role of culture, we exploit the language divide in bilingual cantons as a source of exogenous variation within the canton. In particular, we use a spatial RDD contrasting the dependency levels at entry in nursing homes of individuals living on opposite sides of the linguistic border (controlling for canton fixed effects). In determining the impact of culture on the demand for social insurance, Eugster et al. (2011) adopt a fuzzy RDD exploiting the jump in the probability of speaking French across the two sides of the linguistic border. According to their estimates, the share of the French speaking population to the West-hand side of the linguistic border is 85%, while the share of the French speaking population to the East-hand side of the linguistic border is about 10%. In our context, we are not aware of the language spoken by the elderly people in the sample. Hence, we refer to Eugster et al. (2011) for the first stage estimates of the fuzzy design, and we only focus on the reduced form.

Following their approach, we define municipalities at the border as those French speaking municipalities bordering with at least one German speaking municipality. The municipality of interest here is the municipality of residence of the elderly person before being institutionalized, not the municipality of the nursing home. Thus, we define the treatment as a dummy variable equal to 1 if the elderly person resided in the French speaking area before entering the nursing home. The assignment (or running) variable is the kilometric travel distance from the municipality of residence to the closest French speaking municipality on the linguistic border. French speaking municipalities at the linguistic border are assigned a distance of 0 from the border, while all the other French speaking municipalities are assigned a positive number. In the same way, all the German speaking municipalities are assigned a negative number.

More specifically, we estimate the following regression:

$$Y_{im} = \beta_0 + \beta_1 F_m + \beta_2 dist_m + \beta_3 Z_{im} + \beta_4 F_m dist_m + \varepsilon_{im} \tag{1.6}$$

where Y_{im} is the dependency level at entry of the individual i residing in municipality m (before entering in the nursing home); F_m is a dummy for French municipalities (our treatment), $dist_m$ is the assignment variable, Z_{im} represents a set of covariates and ε_{im} is a stochastic error term. The coefficient β_1 represents the effect of interest, namely the difference in dependency levels between the French speaking and the German speaking areas at the linguistic border. In the standard regression discontinuity approach, all the control variables should be continuous at the cut-off, and thus control variables are not required. However, in the present setting we control for the canton and the year of entry in nursing homes. Given that LTC policies are set at cantonal level, controlling for cantons is fundamental to ensure a correct comparison of observations across the linguistic border. To the same extent, the year of entry is important to avoid capturing time effects in our average treatment effect. The interaction term between the treatment and the assignment variable accounts for the possibility of different linear trends on either side of the discontinuity.

The effect of interest and the selection of the optimal bandwidth are both computed using the non-parametric procedure developed in Calonico et al. (2014) and Calonico et al. (2016).[10] The non-parametric estimator allows to correct for the bias that might arise imposing the linearity of the fitting line (with robust bias-corrected confidence intervals). The choice of the bandwidth is based on the optimal bandwidth choice proposed by Imbens and Kakyanaraman (2012). However, we also test the robustness of our results to the bandwidth choice and to higher polynomial orders using parametric specifications (see Appendix).

Finally, we evaluate the validity of our identification strategy (i.e., continuity assumption) by testing for the presence of discontinuity at the border for a very large set of covariates (socio-demographic and economic variables) and other relevant variables that, by definition, should be continuous at the border. In particular, we test for discontinuity in the prevalence of the most common diseases. This is meant to verify whether the discontinuity in the dependency level at entry in nursing homes is caused by a discontinuous change in the health conditions at the border rather than different preferences regarding the time of entry in nursing homes, as we argue. Additionally, we test for discontinuity in prices and other supply factors (i.e., insurance contributions and number of nursing home beds) that should be also continuous at the border.

1.6 Results

1.6.1 Regression discontinuity design

We start the analysis by showing the discontinuity in the dependency level at entry at the linguistic border (Figure 1.5). We control for canton fixed effect to account for supply and other institutional differences. Each point in the graph represents the mean residual for a group of municipalities aggregated according to the distance from the linguistic border in the three bilingual cantons. The cloud of bins looks noisy because in some municipalities the number of observations (i.e., number

[10] We use the 2016 version of the Stata command *rdrobust*.

of people who entered a nursing home) is quite low. Moreover, using a bandwidth larger than 30 km implies losing at least one canton on each side of the border.[11] Therefore, we report the full bandwidth in the top figure, while in the bottom figure the analysis is restricted to a bandwidth of 25 km and to municipalities with at least 50 people who entered a nursing home in the period of interest (2007–2013). In the 25-km figure we observe quite a clear jump in the dependency level at entry in nursing homes at the linguistic border (predicted also in the full bandwidth figure). Similarly, Figure 1.6 reports the discontinuity in the share of voters (at municipal level) voting "yes" in the 2013 referendum on family policies after controlling for canton fixed effect. The large discontinuity in referendum outcomes at the linguistic border suggests a large discontinuity in preferences for family policies, which mirrors the differential use of LTC services.

A more formal test of our RDD on the dependency level at entry is presented in Table 1.2. The optimal bandwidth is computed non-parametrically and the results are obtained controlling for canton and year fixed effects.[12] Column (1) displays the estimates of the treatment effect (French border) without accounting for the possibility of the linear fitting bias. Columns (2) and (3) show the estimates of the bias-correction procedure proposed by Calonico et al. (2014) that accounts for the presence of the linear fitting bias in estimating the average treatment effect. The average treatment effect is always positive and statistically significant even with robust bias-corrected confidence intervals (Column (3)). The magnitude of this coefficient accounts for around 10% of the standard deviation. Since our estimates represent a reduced form effect, the coefficient β_1 estimated above should be inflated to take into account the jump in the probability of speaking French at the linguistic border. According to Eugster et al. (2011), the impact of the treatment (i.e. residing in the French speaking region) on the language spoken is 0.754. Hence, the average treatment effect should be multiplied by a factor of 1.327 (1/0.754). In the bias-corrected robust specification, the inflated average treatment effect is 0.13. This means that accounting for the actual probability of residing on one side of the linguistic border and speaking the same language, French speaking people show a 0.13 higher dependency level at entry than German speaking people, which is 13% of the standard deviation. In addition, recalling that each point in our measurement scale of the dependency level corresponds to one hour of care per day, a French-German gap of 0.13 corresponds to 6 more minutes of care per day at entry in the French speaking part. To give

[11] Note that the full bandwidth is not symmetric because the German side spans for almost 150 km, while the French one for less than 80.

[12] As a robustness check, we report the results without controlling for canton and year fixed effects in Table 1.A.1 of Appendix. The magnitude of the coefficient β_1 is almost 4 times larger than the main estimates. This result might be due to canton-specific factors correlated with the language. For instance, some cultural differences may be captured by the canton fixed effect since the three bilingual cantons have a different proportion of German-speaking people (Bern 84%, Friburg 33%, and Valais 29%). In any case, this result confirms the importance of controlling for institutional differences across cantons to disentangle the cultural variation.

a grasp about the magnitude of this effect, 6 minutes per day corresponds to 36.5 hours of care in one year per elderly person in nursing home.

Robustness checks

To check the validity of our non-parametric estimates, we perform a parametric RDD evaluating the sensitivity of the estimated coefficients to different bandwidths (namely 25-km, 50-km and 100-km) and different polynomial orders (up to fourth). The results reported in Table 1.A.2 of Appendix are consistent with those reported in the main text.

We also repeat our non-parametric estimations with two more dependent variables: age at entry (*Age at entry*) and residing at home prior to nursing home entry (*Residing at home*). The regression discontinuity results for these two variables are presented in Table 1.A.3 of Appendix. The point estimate on *Age at entry* is always positive, even though the large standard errors wipe out the significance of the coefficients. This confirms our previous insights, according to which French speaking individuals tend to enter nursing homes at older ages, but this measure is too noisy to find any conclusive evidence. For *Residing at home* the estimated discontinuity at the language border is always negative and statistically significant. This suggests that German speaking individuals enter a nursing home from their home more often than French speaking individuals. This supports our idea of a cultural divide between the two areas. Indeed, people in the French speaking region are more likely to enter a nursing home from hospital or another institution, that is when critical health conditions do not allow to postpone entry anymore.

Continuity assumption

As previously mentioned, control variables and other potential determinants of entrance in a nursing home should be continuous at the cut-off. For this reason, in the Appendix we provide graphical evidence of the continuity of a very large set of variables. In particular, we do not observe evidence of a discontinuity at the linguistic border in gender, mortality rate, share of people 65+, population, home ownership, taxable income, and education (Figures 1.A.3 and 1.A.4). This also allows us to discard some of the most plausible explanations for the observed discontinuity in the dependency level at the linguistic border. Conversely, we do find a discontinuity in the immigration rate and, if we consider a bandwidth larger than 25 km, in the unemployment rate. The close proximity to France explains the higher immigration rate on the French side of the three bilingual cantons. We believe that such discontinuity is not a concern for our identification because we already showed large differences among natives (almost all people in nursing home) in preferences and family values. Regarding the unemployment rate, the relatively large difference between the two language groups fades away as we get closer to the language border. Nevertheless, the estimated discontinuity in the dependency level is not affected when we include these variables as controls in our RDD (Table 1.A.4).

Finally, we use two additional levels of aggregation to further test our main identification assumption. First, we exploit the distance between the municipality of the provider headquarter and the linguistic border to show that there are no discontinuities in clients out-of-pocket expenditure for LTC services, in private insurance contributions and in the number of nursing home beds (Figure 1.A.5). This result is not surprising because we are holding constant the supply factors at cantonal level. Then, we use administrative data at hospital level to test for the presence of discontinuity in diseases (Figure 1.A.2). In particular, we do not find evidence of discontinuities in acute myocardial infarction, hip fractures, strokes, and Parkinson disease, which are frequent among the elderly and likely to affect LTC arrangement decisions.[13]

1.6.2 Mechanisms and alternative explanations

The large battery of tests on the continuity assumption (Figures 1.A.2–1.A.5) allows us to reject several plausible explanations for the discontinuity in the dependency level at the language border. In particular, we show that demographic, socio-economics aspects (demand side), supply-side factors and health conditions are continuous at the language border. Furthermore, following the literature on the determinants of LTC choices we find no evidence of discontinuity in home ownership.

Clearly, most of the evidence reported so far comes from aggregate data at municipal level and does not allow to investigate other household characteristics that affect LTC choices and to focus on households with elderly people. For this reason, in Table 1.3, we investigate whether there are differences between the two language groups in several household characteristics. We use census data (PUS) and focus only on the three bilingual cantons. Although differences in family values could affect the household structure, we do not find evidence of large differences in the household size between the two linguistic groups, both unconditional (Column (1)) and conditional on respondents 65+ (Column (2)). Moreover, focusing only on 65+ respondents we do not find differences in the probability of living alone (Column (3)) or with a partner (Column (4)). Finally, in Column (5) we show that there are no differences in the probability of living with parents for adult respondents (aged 30–64).

Family value and informal care

We already documented large differences in family values between the two cultural groups in Fig-

[13]We also investigate other diseases but their prevalence does not allow to provide a meaningful test of the continuity at the linguistic border.

ure 1.1. Also, the figure suggests that Latin speaking individuals consider elderly care a family duty and spend more time taking care of other family members. Furthermore, political preferences (i.e. referendum votes) on family policies are strongly correlated with the language. Finally, using data from the Swiss Household Panel we find that Latin respondents declare to have more frequent contacts with both children and relatives than German respondents (see Table 1.A.5).[14] This supports the interpretation that the language spoken captures the cultural variation in preferences about the family.

We argue that these differences in family values and ties explain why people from Latin speaking areas enter a nursing home in worse health conditions than their German neighbors. Strong family ties may lead people to postpone entrance in nursing home because people prefer to stay with their family members as long as possible. However, home care arrangements require that medical and personal care is carried out at home with formal or informal care services. We already showed that in Latin speaking districts there is a larger use of home care services (Figure 1.4). Moreover, we expect that informal care is also more widespread in Latin speaking regions because help at home for ADL and IADL is generally not covered by health insurance. Unfortunately, we do not have data on informal care that allow us to show evidence of discontinuity at the language border in the provision of informal care. Despite this, we can take advantage of survey data from SHARE focusing on the two Swiss NUTS2 regions that include our bilingual areas.[15]

Table 1.4 shows that Latin speaking respondents living in these two regions receive and provide more informal care than their German counterpart. In particular, Latin respondents receive more care from both household members and relatives outside the household, and they also provide more care to other family members or to grandchildren. This difference is robust to the inclusion of potential confounders such as age, sex, education and area characteristics (rural vs. urban). By comparing the results of Table 1.3 and 1.4, it is interesting to note that individuals speaking a Latin language provide more informal care, even though the household size is not statistically different between the two areas (if ever, it is smaller in the French speaking area). This evidence further corroborates our argument that observed differences in LTC arrangement choices between the two cultural areas should be driven by different family values.

[14] More details regarding Swiss Household Panel data are provided in the Appendix (see the notes of Table 1.A.5).

[15] For consistency with our main analysis, we only use data from respondents living in the bilingual NUTS2 regions: CH01 (Vaud, Valais, and Geneva) and CH02 (Berne, Fribourg, Solothurn, Neuchatel, Jura). The Nomenclature of Territorial Units for Statistics (NUTS) is a standard geocode for referencing the subdivision of countries for statistical purposes.

1.7 Discussion

This paper investigates the role of culture in shaping LTC arrangement decisions. We use data from Switzerland, a multi-cultural confederation of 26 states and four languages, where the two main linguistic groups —Latin and German— are characterized by large differences in family values and opinions about the role of family in taking care of the elderly.

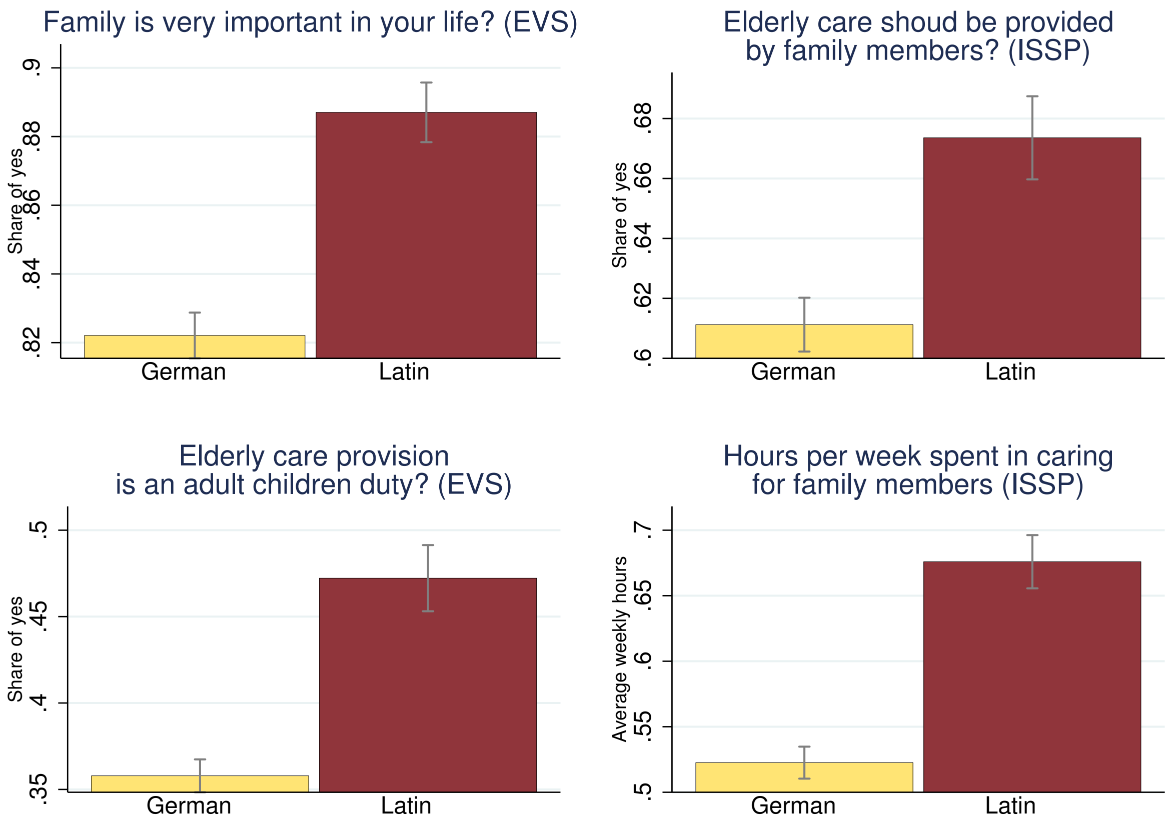
To identify the impact of culture, we perform a spatial RDD at the linguistic border of the three French and German speaking bilingual cantons. We find that people residing in the French speaking part of the country enter a nursing home with higher dependency level as compared to people residing in the German speaking areas. Adopting different parametric and non-parametric specifications, we find that the French-German gap in the dependency levels at entry corresponds to 6 more minutes of care per day in the French speaking areas (i.e., 36.5 more hours of care in a year per elderly person in nursing home), and accounts for roughly 13% of the standard deviation.

The reported evidence of a strong (causal) influence of culture on the Swiss LTC market may also contribute to explain the large cross-country variation in the size of LTC markets. This is particularly relevant for Europe, where cultural differences about the role of family show a clear North-South gradient.

Our findings may have important policy implications. Public policies that incentivize specific LTC arrangements may lead to different behavioral responses in the population according to predominant preferences. In other words, increasing the provision of specific elderly care arrangements without a careful evaluation of the demand-side response may not be sufficient to expand their use. For example, in Switzerland between 27% and 56% of days spent in nursing homes in 2013 involved people with very low need of care. Notably, experts argue that people receiving between one and two hours of daily care could be cared more efficiently with formal home-based services than in nursing homes (Wächter and Künzi, 2011). However, given their stronger preferences for nursing home care, German speaking individuals with mild health problems may still be better off entering a nursing home, even though it would be more cost-effective from the society viewpoint to grant them care at home. Therefore, expanding formal home-based care provision in German speaking areas may not trigger an increase in home-based care use per se.

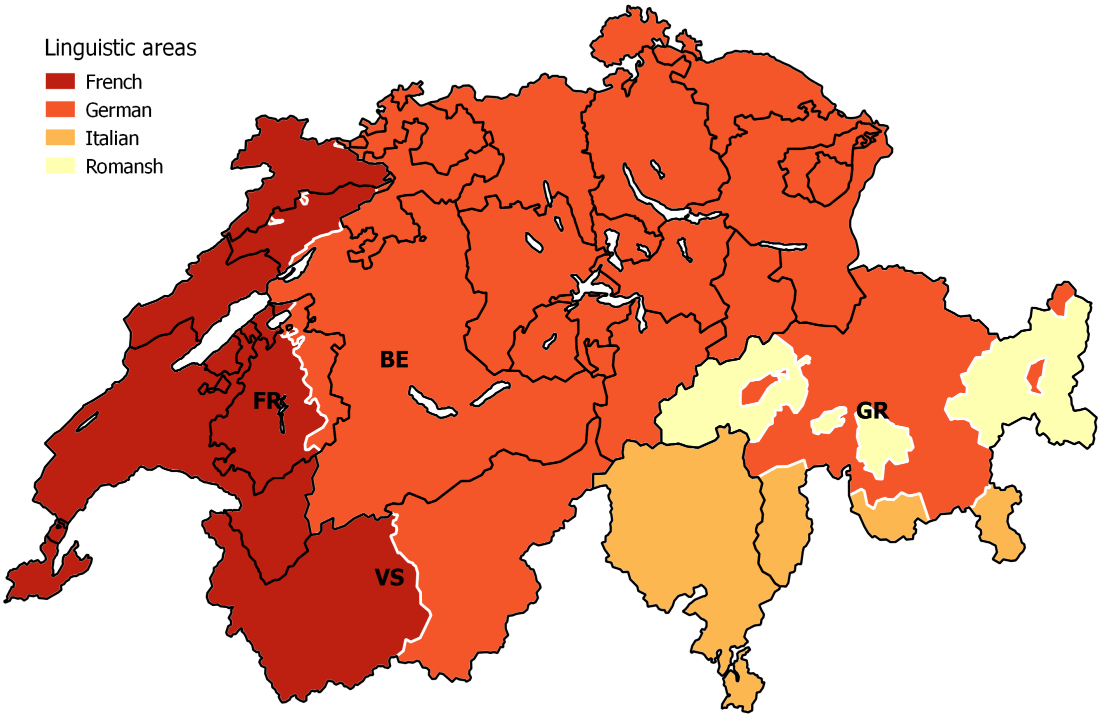
Finally, our results suggest that the availability of substitutes for elderly care may be endogenous to culture. Many empirical studies investigating the substitutability between formal and informal services use the presence of other people in the household or the presence of children living within a certain distance from the household as an instrument for the provision of informal care. However, French speaking individuals provide more informal care even in the absence of systematic differences in household size. This suggests that the availability of substitutes for formal care per se does not trigger the provision of informal care.

Figure 1.1: Cultural attitudes in Latin and German speaking areas towards family and elderly care



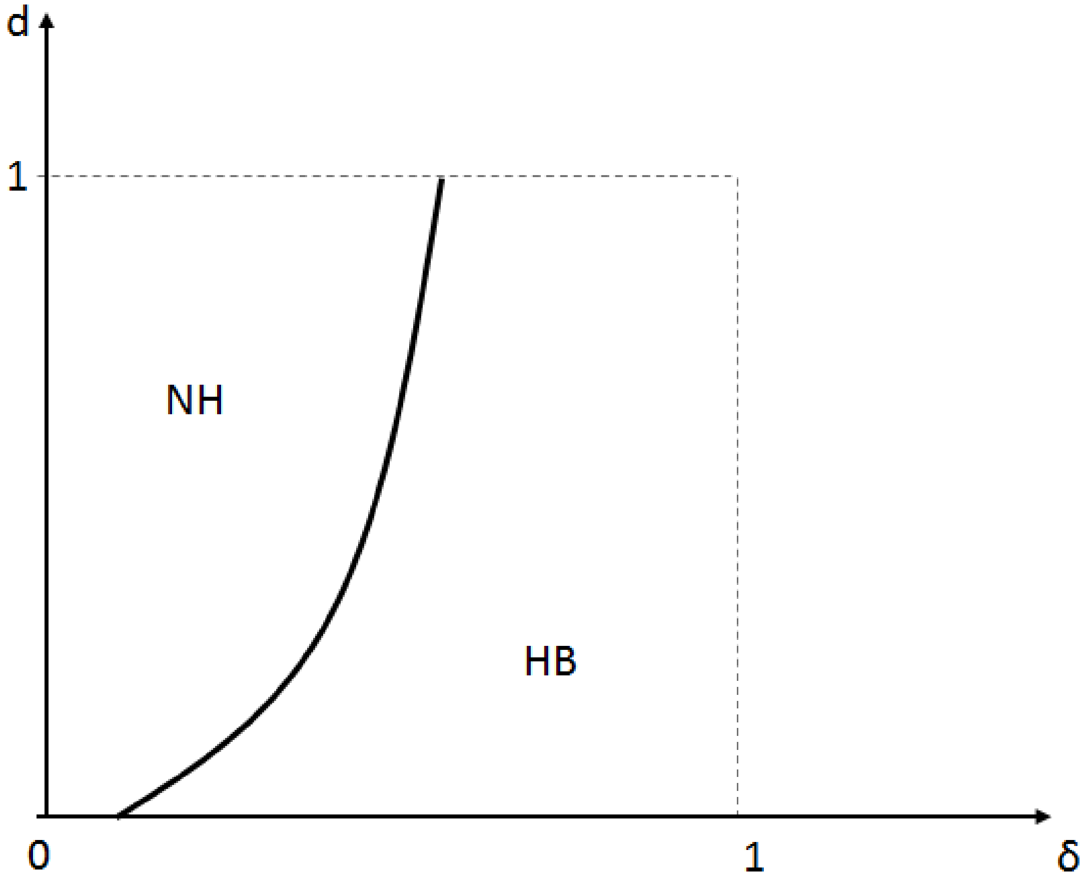
Notes - Sources: These figures are based on data from the 2008 Swiss sample of the European Value Survey (EVS) and from the 2012 Swiss sample of the International Social Survey Programme (ISSP). The EVS includes 1'238 respondents (937 Germans + 301 Latins), while the ISSP includes 1'198 respondents (892 Germans + 306 Latins). Each graph shows the Latin-German gap after conditioning on age (full set of age dummies), sex and education. Top-left: EVS - Question 2: "How important is the family in your life?"; Top-right: ISSP - Question 14: "Thinking about elderly people who need some help in their everyday lives, such as help with grocery shopping, cleaning the house, doing the laundry etc. Who do you think should primarily provide this help?"; Bottom-left: EVS - Question 51a: "Which of the following statements best describes your views about responsibilities of adult children towards their parents when their parents are in need of long-term care? Adult children have the duty to provide long-term care for their parents even at the expense of their own well-being."; Bottom-right: ISSP - Question 16b: "On average, how many hours a week do you spend looking after family members? (e.g. children, elderly, ill or disabled family members?)". Results are substantially unchanged even conditional on standard demographic and socio-economic controls (i.e., age, sex, education, employment status).

Figure 1.2: Linguistic areas across Switzerland



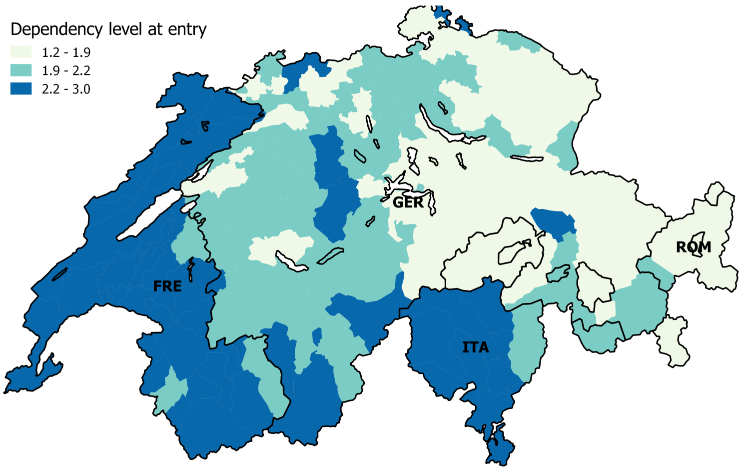
Notes - Colors correspond to different linguistic areas. In order from the darkest color to the lightest color: French speaking area, German speaking area, Italian speaking area, and Romansh speaking area. Dark lines correspond to cantonal borders while white lines highlight linguistic borders that do not coincide with cantonal borders. Cantonal labels are reported only for bilingual and trilingual cantons and correspond to: BE - Bern; FR - Fribourg; GR - Graubünden; VS - Valais.
Sources: Base maps: ©OFS, ThemaKart.

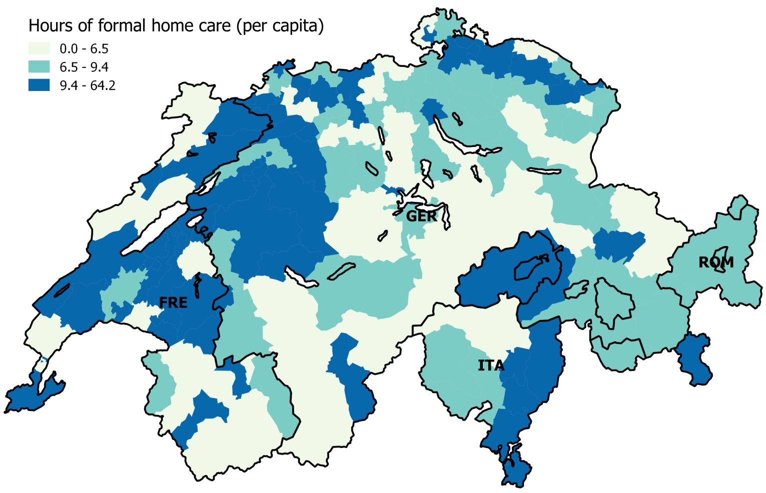
Figure 1.3: Relationship between dependency level and preference parameter for home-based care



Notes - Graph drawn according to the functional form $p_h(d) = \alpha + \beta d$, where α can be interpreted as the fixed component of home-based care price with respect to the severity of the elderly person health condition, and β can be interpreted as the variable component of home-based care price with respect to the severity of the elderly person health condition. Then, $d^* = \frac{\delta(p_n+\alpha)-\alpha}{(1-\delta)\beta}$.

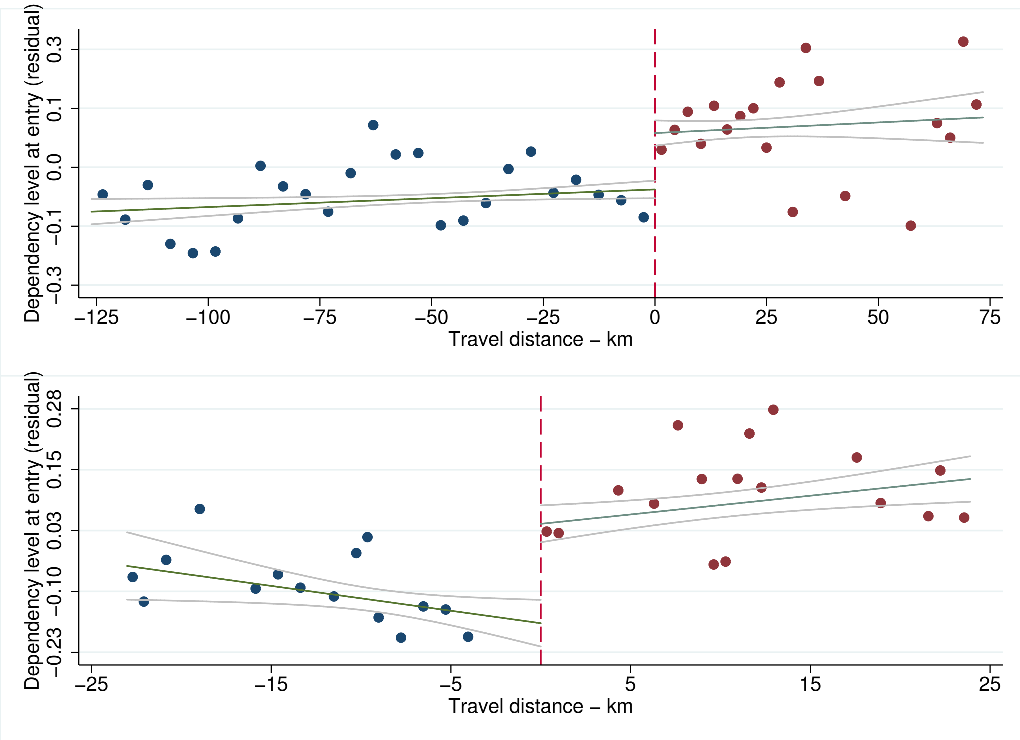
Figure 1.4: Dependency level at entry and share of people over 65 in formal home-based care by district and linguistic area in 2013





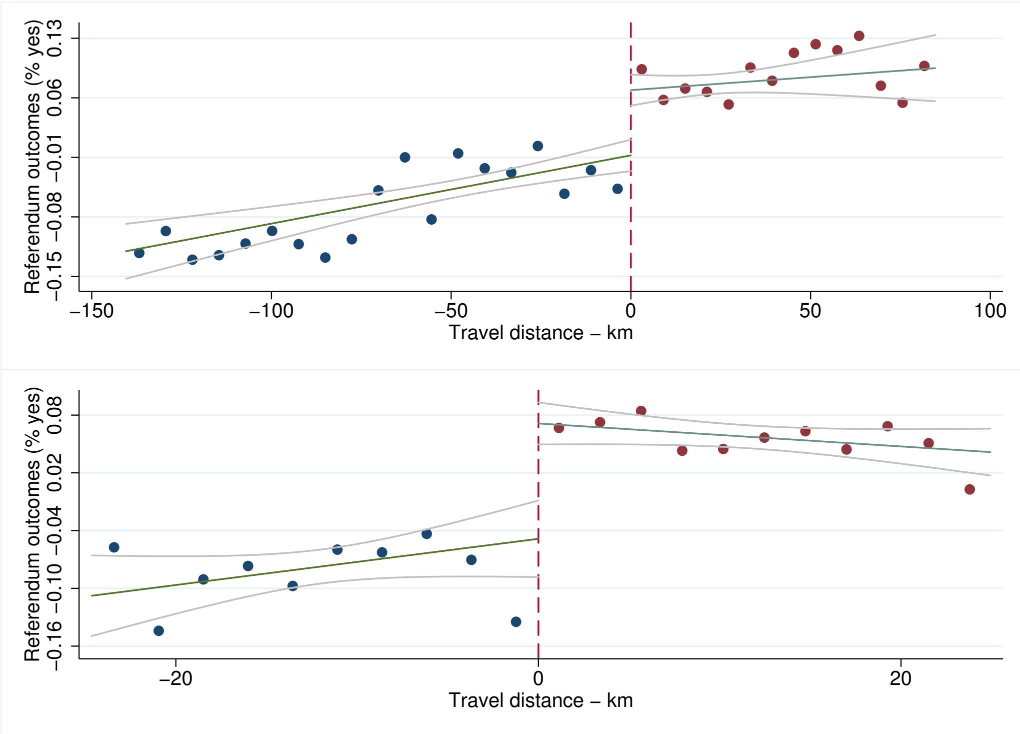
Notes - The map reports the average dependency level at entry in nursing home (top) and the average number of hours of home-based care per person aged 65 or more (bottom) by district in 2013. Intervals depicted in different colors correspond to the terciles of average hours of formal home-based care (per capita) by district. Black borders delimit linguistic areas: FRE - French, GER - German, ITA - Italian, ROM - Romansh.
Sources: Base maps: ©OFS, ThemaKart; Data: SOMED and HCS - year 2013.

Figure 1.5: Distribution of dependency level at entry across the linguistic border



Notes - This graph is based on individual data from the three bilingual cantons of Berne, Fribourg and Valais for the period 2007-2013, and is adjusted for cantonal and year fixed effect. The top graph includes all people from all municipalities, while the bottom graph includes only people that used to live within 25 km (travel distance) from the language border. The number of bins is automatically computed by the *cmogram* command of Stata 14 and corresponds to $\#bins = min\{sqrt(N), 10{*}ln(N)/ln(10)\}$, where N is the (weighted) number of observations. We exclude from the figure extreme values (top and bottom 1% of the dependency level distribution) and individuals from municipalities with less than 50 observations. Positive values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for French speaking municipalities. Negative values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for German speaking municipalities. French speaking municipalities at the linguistic border are assigned a distance of 0 from the linguistic border.
Sources: Elaboration on SOMED data - years 2007-2013.

Figure 1.6: Distribution of preferences for family policies across the linguistic border - 2013 referendum outcomes



Notes - The referendum was about the approval of an amendment to the Swiss Constitution committing the cantons to provide complementary day care facilities to help the reconciliation between work and family duties, and allowing the Confederation to intervene whenever cantonal efforts are insufficient. This graph is based on municipal data from the three bilingual cantons of Berne, Fribourg and Valais, and is adjusted for cantonal fixed effect. The top graph includes all the municipalities, while the bottom graph includes only municipalities within 25 km (travel distance) from the language border. The number of bins is automatically computed by the *cmogram* command of Stata 14 and corresponds to $\#bins = min\{sqrt(N), 10 * ln(N)/ln(10)\}$, where N is the (weighted) number of observations. Positive values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for French speaking municipalities. Negative values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for German speaking municipalities. French speaking municipalities at the linguistic border are assigned a distance of 0 from the linguistic border.
Sources: Elaboration on Swiss Federal Statistical Office data - year 2013.

Table 1.1: Descriptive statistics: individual level data in the three bilingual cantons

	French			*German*			t-test
Variable	Obs.	Mean	S.D.	Obs.	Mean	S.D.	P-value
Dependency level at entry	10,189	2.58	1.01	31,413	1.93	.95	0.000***
Age at entry	10,189	83.93	7.94	31,413	83.85	8.25	0.505
Gender	10,189	.33	.47	31,413	.34	.47	0.311
Residing at home	9,965	.33	.47	30,619	.57	.50	0.000***

Notes - *Dependency level at entry* is measured on a scale from 0 to 4, *Age at entry* is a discrete variable from 50 onwards, *Gender* is a dummy variable equal to 1 for men, and *Residing at home* is a dummy variable equal to 1 if the elderly person was residing at home prior to institutionalization, and 0 if he/she entered the nursing home from a hospital or from another institution. All these variables are drawn from SOMED. The data refer to the cantons of Berne, Fribourg and Valais for the period 2007-2013 and are reported at individual level. The number of observations for *Residing at home* is lower because of missing values. P-value refers to a t-test for mean comparison between French speaking and German speaking individuals. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are robust and clustered at municipal level.

Table 1.2: Non-parametric Regression Discontinuity Design

Variable	Conventional (1)	Bias-corrected (2)	Robust (3)
		Dependency level at entry	
French border (β_1)	.106***	.103***	.103**
	(.04)	(.04)	(.05)
Observations on the East	5,400	5,400	5,400
Observations on the West	5,828	5,828	5,828
Bandwidth	19.91	19.91	19.91
Mean of dependent variable	2.34	2.34	2.34
Std. dev. of dependent variable	1.02	1.02	1.02
Canton fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes - All the estimates are based on individual level data from the three bilingual French and German speaking cantons of Berne, Fribourg and Valais for the period 2007-2013. The dependent variable *Dependency level at entry* is measured on a 0-4 scale. The assignment variable is the kilometric travel distance from the closest French speaking municipality on the linguistic border. Controls include year of entry and canton of residence prior to institutionalization. The number of observations refer to the number of individuals respectively on the East and on the West of the linguistic border. The number of municipalities on the East of the linguistic border is 80 while the number of municipalities on the West is 107. In Figure 1.A.6 in Appendix we also show the distribution of municipalities across the linguistic border. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at municipal level. Estimates are performed using the Stata command *rdrobust*.

Table 1.3: Household composition (PUS 2000)

Dep. variable:	Hh. size	Hh. size	Single	Partner	Parents
Sample:	All	65+	65+	65+	30–64
	(1)	(2)	(3)	(4)	(5)
Latin language	-.073*	-.124	.007	.001	-.005
	(.038)	(.143)	(.012)	(.012)	(.003)
Observations	62,348	11,230	11,230	11,230	29,446

Notes - Data are drawn from Public use sample (PUS) of the 2000 Swiss census. We only include Swiss respondents from the three bilingual cantons of Berne, Fribourg and Valais. Each column reports the results of different regressions of *Latin language* on different variables and samples: (1) household size – the full sample; (2) Household size – 65+ sample; (3) Single household – 65+ sample; (4) living with a partner – 65+ sample; (5) Living with parents in the household – 30–64 sample. *Latin language* is a dummy for the language of the interview, i.e. whether the questionnaire was completed in French (Latin) or German. Each regression also controls for age, sex, canton fixed effects and a dummy for rural areas. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Table 1.4: Language and informal care in bilingual regions (SHARE data)

	Care from hh. members	Care from family (no hh.)	Care to hh. members	Looking after grandchildren
	(1)	(2)	(3)	(4)
Latin language	.016*	.071**	.125***	.133***
	(.010)	(.026)	(.035)	(.048)
Observations	891	752	752	365

Notes - Data are from wave 4 of SHARE. We only include Swiss respondents aged 50+ from the NUTS2 regions: CH01 (Vaud, Valais, and Geneva) and CH02 (Berne, Fribourg, Solothurn, Neuchâtel, Jura). Each column reports the result from probit regressions of *Latin language* on four different dummy variables: (1) the respondent received care from household members; (2) the respondent received care from family members outsides the household; (3) the respondent provided care to household members; (4) the respondent looked after grandchildren. *Latin language* is a dummy for the language of the interview, i.e. whether the questionnaire was completed in French (Latin) or German. Each regression also controls for age (quadratic), sex, education (5 dummies) and a dummy for rural areas. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Appendix

1.A Appendix (for online publication)

1.A.1 Measuring the dependency level at entry

The measurement instruments adopted to evaluate the dependency level of elderly people in nursing homes vary within and between cantons and over time. In particular, there are three instruments. The PLAISIR is mainly adopted in French-speaking cantons and reflects the intensity of care required by elderly people. Conversely, the other two instruments, BESA and RAI-RUG, reflect the intensity of care actually provided to elderly people. Since care requirements may not correspond to the level of care actually provided, the PLAISIR instrument may slightly overestimate the dependency level of elderly people at entry. Therefore, a harmonization of the instruments is necessary. In 2011 an instrument harmonization effort was made by the Swiss assembly of cantonal health care department directors. Thus, a uniform measurement instrument is in place since 2011. Using the suggested conversion procedure we harmonize the intensity of care from different instruments adopted before 2011. Moreover, there are two versions of the BESA instrument: the first one uses a scale from 0 to 12, and each level of the scale corresponds to 20 minutes of daily care; the second one ranges from 0 to 4, and each level of the scale corresponds to 1 hour of daily care. Therefore, we collapse all the scale values into a broader measurement scale, ranging from 0 to 4.

Following the harmonization of measurement instruments and scales, we assess the dependency level at entry for each nursing home resident. We focus on the initial event of care received after entry. We also perform a robustness check using the most intensive event of care received during the year of entry rather than the very first care, and obtain the same results.

Several nursing home residents show repeated entry-exit spells in the period considered, either in the same nursing home or in different nursing homes (around 4% of individuals). Therefore, to consider the most correct entry date, we exclude temporary residents.[16] Also, we deal with repeated spells applying a simple algorithm. We keep the first entry date if the individual does not

[16] Nursing homes may host temporary patients needing a rehabilitation period after hospitalization or elderly people joining daily activities who are not actually residing in the nursing home.

go back home for more than 6 months. This means that for individuals admitted to hospital after institutionalization and then re-entered the nursing home, we consider the first entry date as the actual entry date. Conversely, for individuals who go back home for more than 6 months before entering again, we exclude the first spell and we apply the same criterion to the second entry date. For individuals who go back home for more than 6 months even after the second spell, we also exclude the second spell and apply the same criterion to the third spell, and so on. Of course, for individuals who stay for more than one year and then go back home for more than 6 months before entering again, we keep the first entry date.

Finally, we consider that the provision of care may not have started immediately after the date of entry in a nursing home. Since our data only report the ending date of care, people entering a nursing home in the last part of the year may be disproportionately likely to show no care received in the year of entry. To avoid wrong imputation, for elderly people who enter a nursing home between October and December and do not show any care event until the end of the year, we consider the first care event received in the second year.

1.A.2 Description of variables

Individual level data (from SOMED)

Dependency level: Discrete variable ranging from 0 to 4. 0 corresponds to no care required and each additional unit corresponds to one hour of daily care. A dependency level of 4 corresponds to 4 or more hours of care per day.
Age at entry: Discrete variable. Only clients entering the nursing home at 50 years old or more are included in the sample.
Gender: Dummy variable equal to 1 for men.
Residing at home: Dummy variable equal to 1 if the elderly person resided at home before entering a nursing home and equal to 0 if the elderly person was in a hospital or in another institution.

Municipal level data (sources in parenthesis)[17]

Referendum (% 'yes') (FSO): Share of people voting 'yes' to the 2013 referendum on family policies. The referendum was about the approval of an amendment to the Swiss Constitution committing the cantons to provide complementary day care facilities to help the reconciliation between

[17]FSO stands for Federal Statistical Office; FTA stands for Federal Tax Administration.

work and family duties, and allowing the Confederation to intervene whenever cantonal efforts are insufficient.

Mortality rate (FSO): Number of deaths per municipality out of municipal population.

Share of people above 65 (FSO): Share of people above 65 years old out of municipal population. Since population data by age are not available before 2010, we project the share of elderly people in 2010 on the population between 2007 and 2009.

Population (FSO): Number of municipal residents.

Immigration rate (FSO): Number of foreign residents out of municipal population.

Birth rate (FSO): Number of new births out of municipal population.

Home ownership rate (FSO): Share of people owning their dwelling by municipality.

Unemployment rate: Share of unemployed out of municipal population. Since unemployment data could not be disaggregated at municipal level for municipalities that underwent a merger before 2016, this variable is only available for 2016.

Taxable income (FTA): Logarithm of per capita municipal income.

Share tertiary education (FSO): Share of municipal residents with tertiary education.

Altitude (FSO): Average between the minimum and the maximum elevation of the municipality.

Religion (FSO): Share of catholics out of total municipal population.

Provider level data (sources in parenthesis)

Nursing homes - client out-of-pocket (SOMED): Client out-of-pocket expenditure by nursing home divided by the number of nursing home clients. Before 2011 this variable was not available.

Share over 65 in nursing home (SOMED): Number of people above 65 years old residing in a nursing home out of population above 65 years old residing in the district.

Home care - client out-of-pocket (HCS): Client out-of-pocket expenditure by provider divided by the provider number of clients. Before 2011 this variable was not available.

Home-care hours (HCS): Number of hours of formal home-based care provided by district out of population above 65 years old residing in the district.

LTC insurance contribution (SOMED and HCS): Sum of insurance contributions for nursing home and home-based care divided by the sum of nursing home and home care clients. Before 2011 this variable was not available.

Nursing homes - number of beds (SOMED): Number of beds for long stayers in nursing homes.

MEDSTAT level data (hospital admission data)[18]

Incidence of AMI (Acute Miocardial Infarction): Number of hospital admissions for AMI out of medstat population.

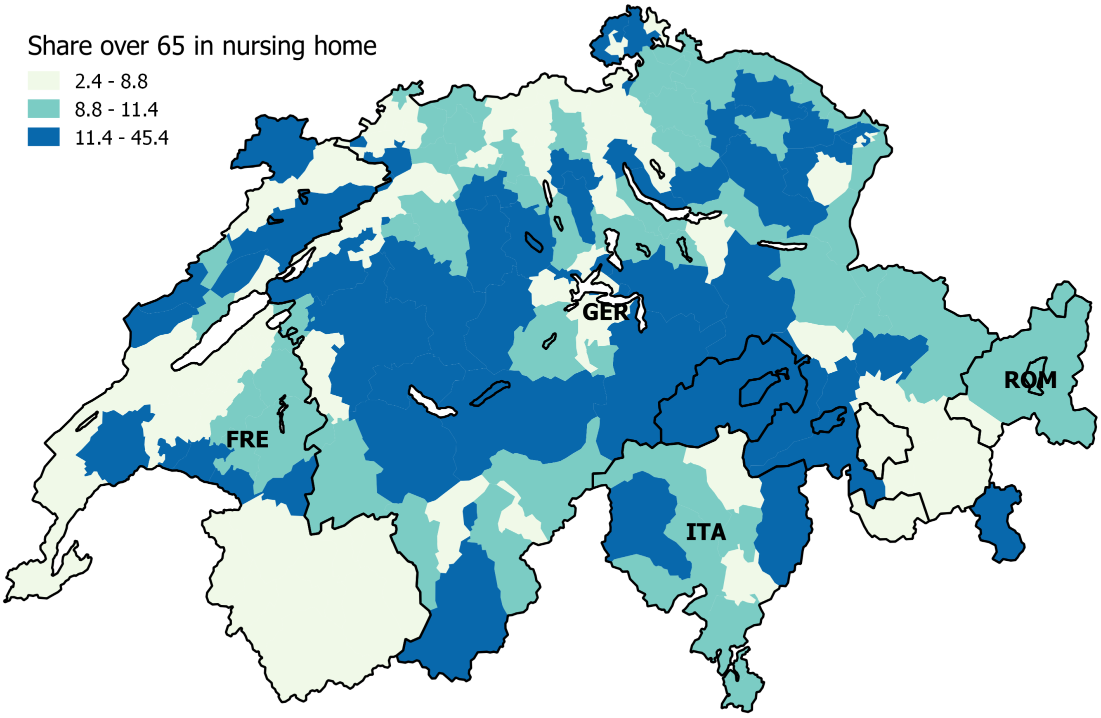
Incidence of hip fractures: Number of hospital admissions for hip fracture out of medstat population.

Incidence of strokes: Number of hospital admissions for stroke out of medstat population.

Incidence of Parkinson disease: Number of hospital admissions for Parkinson disease out of medstat population.

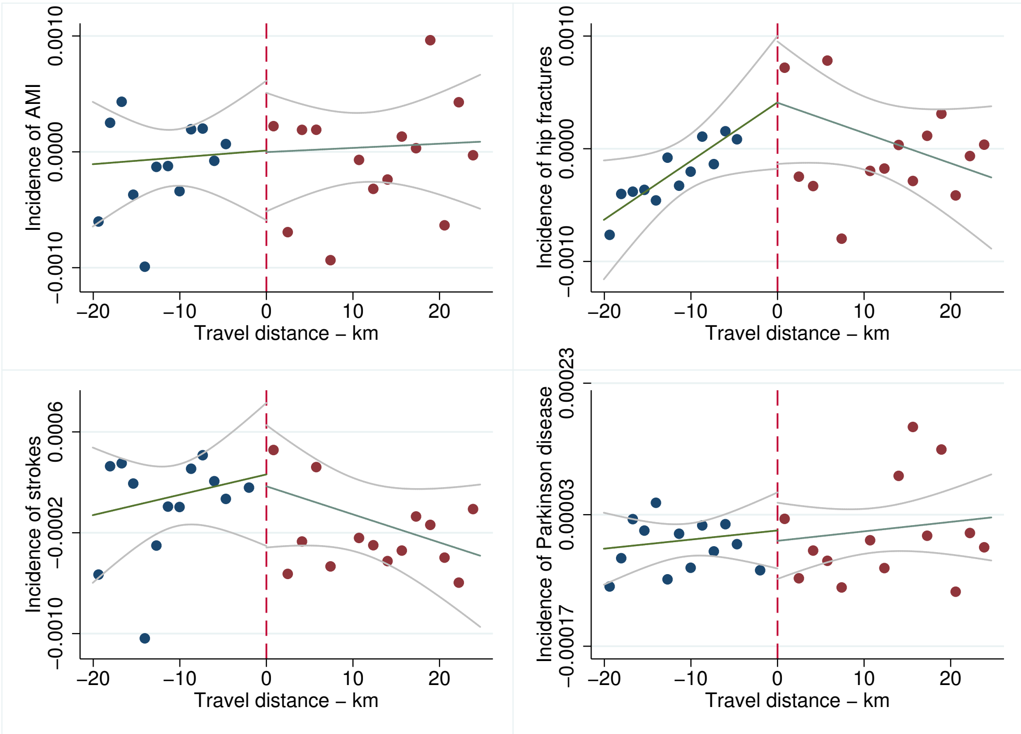
[18]Medstats are geographical units defined according to postal codes. Since we only have population at municipal level, whenever a municipality overlaps several medstats we assign an equal share of municipal population to all the medstats involved.

Figure 1.A.1: Percentage of people over 65 in nursing homes by district and linguistic area in 2013



Notes - The percentage of people in nursing homes is computed dividing the number of people above 65 years old residing in a nursing home by the number of people above 65 years old residing in the district. Intervals depicted in different colors correspond to the terciles of the percentage of people above 65 residing in a nursing home by district. Black borders delimit linguistic areas: FRE - French, GER - German, ITA - Italian, ROM - Romansh.
Sources: Base maps: ©OFS, ThemaKart; Data: SOMED - year 2013.

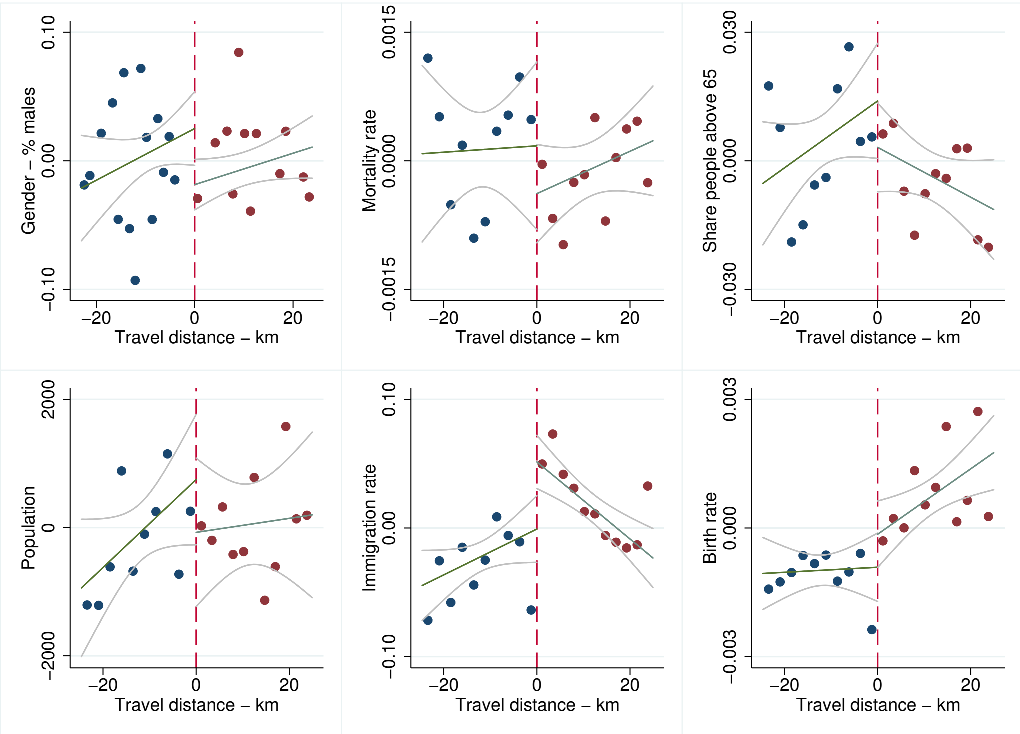
Figure 1.A.2: Distribution of diseases across the linguistic border (hospital admission data)



Notes - The graphs are based on provider-level data from the three bilingual cantons of Berne, Fribourg and Valais for the period 2007-2012, and are adjusted for cantonal fixed effects. For hospital data the unit of observation is the medical statistical unit (medstat), which is defined in terms of postal codes. We derive the distance of each medstat from the linguistic border averaging the distances of the municipalities within the medstat. The number of bins is set manually to 15 on each side of the discontinuity, and the graph is performed using the Stata command *cmogram*. Positive values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for French speaking municipalities. Negative values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for German speaking municipalities. French speaking municipalities at the linguistic border are assigned a distance of 0 from the linguistic border. The number of cases is normalized according to each medstat population.

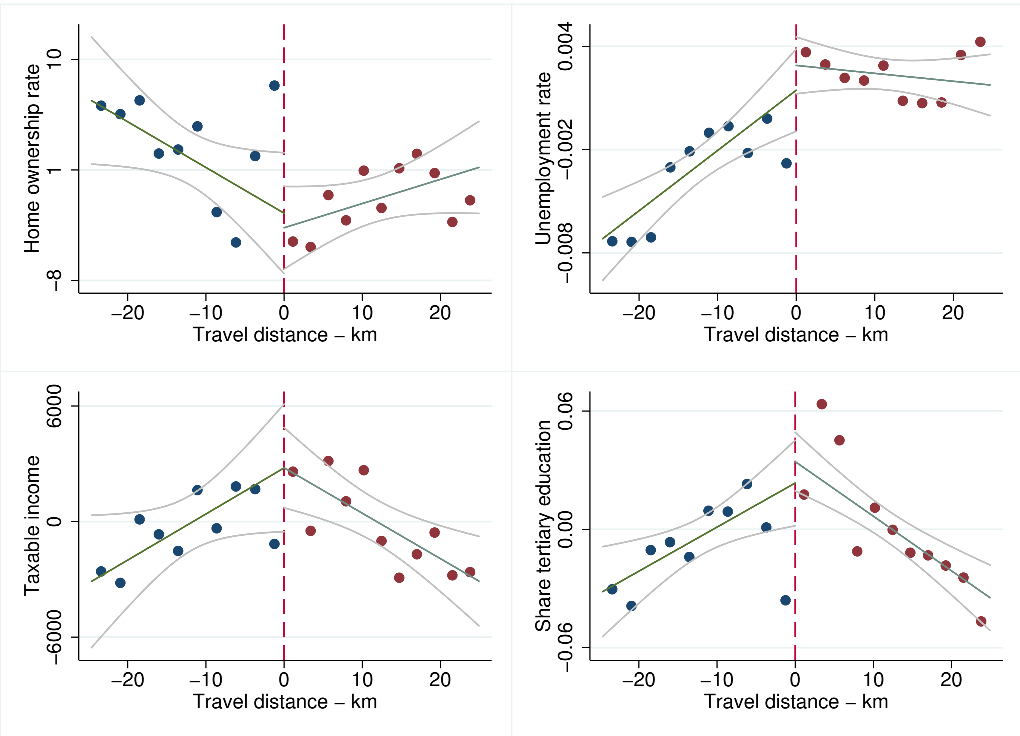
Sources: Elaboration on hospital admission data - years 2007-2012.

Figure 1.A.3: Distribution of demographic variables across the linguistic border (individual or municipal level)



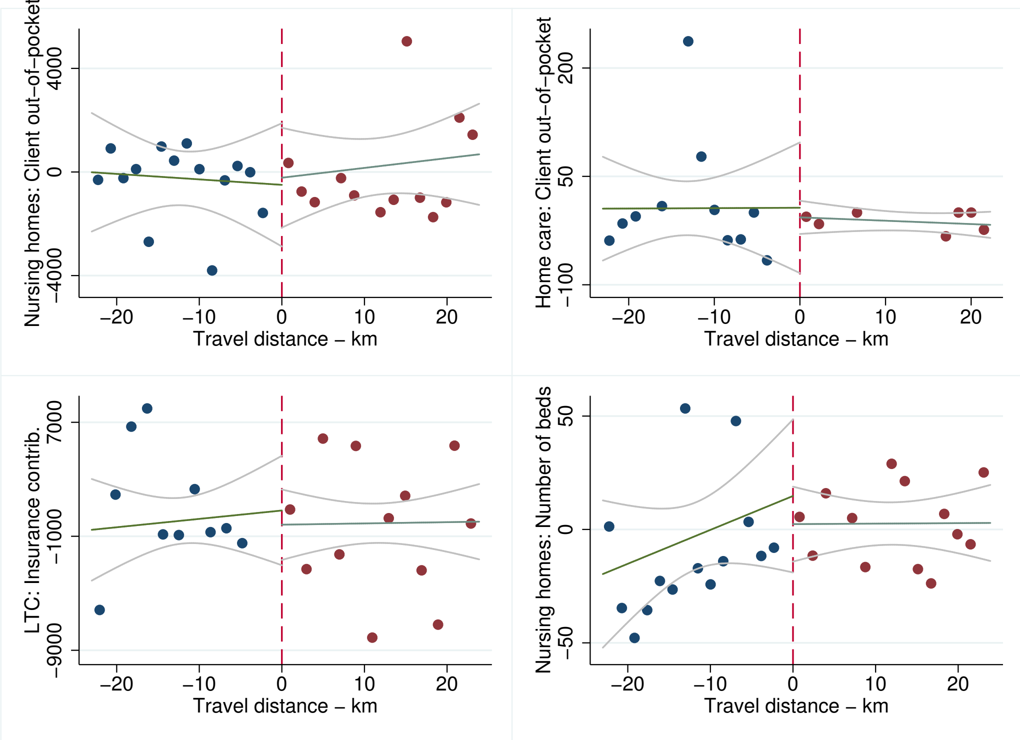
Notes - The graph for gender (top-left) is based on SOMED individual data for the three bilingual cantons of Berne, Fribourg and Valais for the period 2007-2013, and is adjusted for cantonal and year fixed effects. The other graphs are based on municipal data from the three bilingual cantons of Berne, Fribourg and Valais for the period 2007-2013, and are adjusted for cantonal fixed effects. The number of bins is automatically computed by the *cmogram* command of Stata 14 and corresponds to $\#bins = min\{sqrt(N), 10 * ln(N)/ln(10)\}$, where N is the (weighted) number of observations. Positive values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for French speaking municipalities. Negative values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for German speaking municipalities. French speaking municipalities at the linguistic border are assigned a distance of 0 from the linguistic border.
Sources: Elaboration on SOMED and Swiss Federal Statistical Office data - years 2007-2013.

Figure 1.A.4: Distribution of socio-economic variables across the linguistic border (municipal level)



Notes - The graphs are based on municipal data from the three bilingual cantons of Berne, Fribourg and Valais for the period 2007-2013, and are adjusted for cantonal fixed effects. Income data are only available up to 2012, while unemployment data are only available for 2016. The number of bins is automatically computed by the *cmogram* command of Stata 14 and corresponds to $\#bins = min\{sqrt(N), 10 * ln(N)/ln(10)\}$, where N is the (weighted) number of observations. Positive values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for French speaking municipalities. Negative values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for German speaking municipalities. French speaking municipalities at the linguistic border are assigned a distance of 0 from the linguistic border.
Sources: Elaboration on Swiss Federal Statistical Office data and Federal Tax Administration data - years 2007-2013.

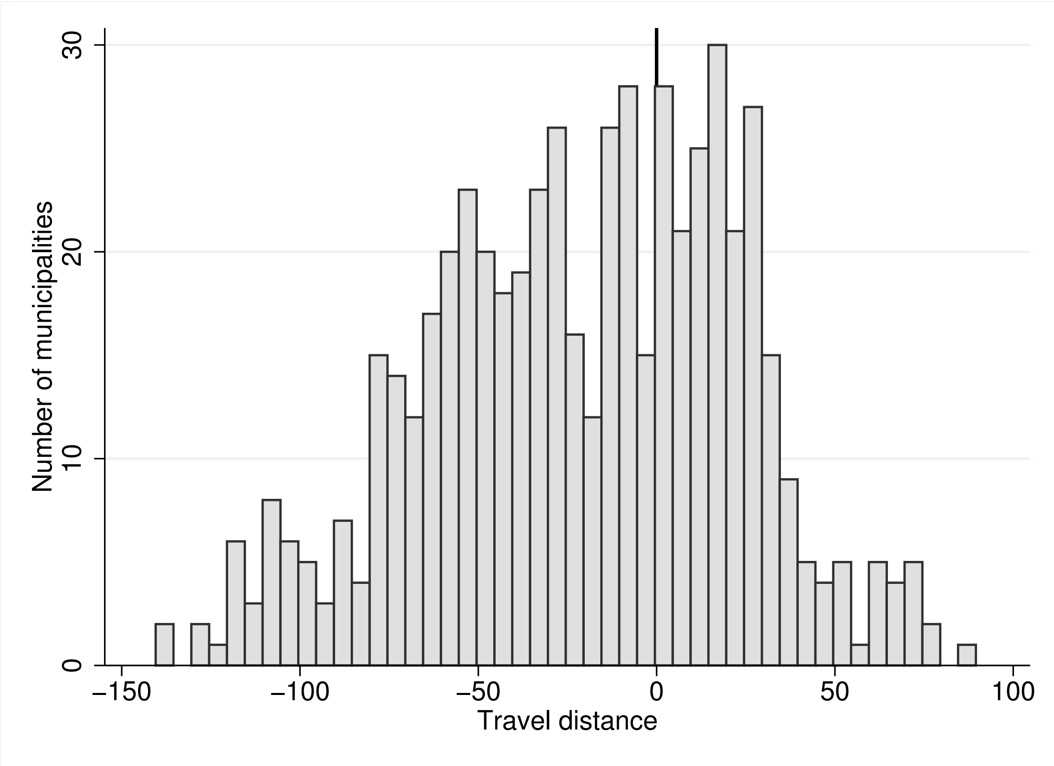
Figure 1.A.5: Distribution of supply-side variables across the linguistic border (provider level)



Notes - The graphs are based on provider-level data from the three bilingual cantons of Berne, Fribourg and Valais, and are adjusted for cantonal fixed effects. Data about client out-of-pocket expenditure and private insurance contributions are only available since 2011. The graph about the number of beds is based on the whole period, 2007-2013. The graph about home care client out-of-pocket expenditure is based on the cantons of Berne and Valais, since this value was 0 for all the providers in Fribourg. Figures for client out-of-pocket expenditure and private insurance contributions only refer to medical care costs. Residential costs or ADL and IADL costs are not included. Each provider is assigned a kilometric distance from the linguistic border according to the municipality of its headquarter. The number of bins is set manually to 15 on each side of the discontinuity and the graph is performed using the Stata command *cmogram*. Positive values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for French speaking municipalities. Negative values on the x-axis correspond to the kilometric travel distance from the closest French speaking municipality on the linguistic border for German speaking municipalities. French speaking municipalities at the linguistic border are assigned a distance of 0 from the linguistic border.

Sources: Elaboration on SOMED and HCS data - years 2007-2013.

Figure 1.A.6: Distribution of municipalities across the linguistic border



Notes - This graph represents the number of municipalities according to the kilometric travel distance from the linguistic border. Each bar corresponds to a 5-km bandwidth.
Sources: Elaboration on FSO data.

Table 1.A.1: Non-parametric Regression Discontinuity Design without controls

Variable	Conventional (1)	Bias-corrected (2)	Robust (3)
	Dependency level at entry		
French border (β_1)	.389***	.419***	.419***
	(.09)	(.09)	(.11)
Observations on the East	3,704	3,704	3,704
Observations on the West	3,484	3,484	3,484
Bandwidth	10.22	10.22	10.22
Mean of dependent variable	2.29	2.29	2.29
Std. dev. of dependent variable	1.02	1.02	1.02
Canton fixed effects	No	No	No
Year fixed effects	No	No	No

Notes - All the estimates are based on individual level data from the three bilingual French and German speaking cantons of Berne, Fribourg and Valais for the period 2007-2013. The dependent variable *Dependency level at entry* is measured on a 0-4 scale. The assignment variable is the kilometric travel distance from the closest French speaking municipality on the linguistic border. Estimates are performed using the Stata command *rdrobust*. Observations refer to the number of individuals. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at municipal level.

Table 1.A.2: Parametric Regression Discontinuity Design

Variable	(1)	(2)	(3)	(4)	(5)	(6)
			Dependency level at entry			
French border (β_1)	.123**	.094*	.141***	.106**	.016	.154**
	(0.05)	(.05)	(.04)	(.05)	(.06)	(.06)
Observations	12,780	27,499	39,988	39,988	39,988	39,988
Dep. var. mean	2.33	2.16	2.10	2.10	2.10	2.10
Dep. var. std. dev.	1.02	1.03	1.01	1.01	1.01	1.01
Bandwidth:	25 km	50 km	100 km	100 km	100 km	100 km
Polynomial fit:	Linear	Linear	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes - All the estimates are based on individual level data from the three bilingual French and German speaking cantons of Berne, Fribourg and Valais for the period 2007-2013. The dependent variable *Dependency level at entry* is measured on a 0-4 scale. The assignment variable is the kilometric travel distance from the closest French speaking municipality on the linguistic border. Estimates are performed using the Stata command *rdrobust*. Observations refer to the number of individuals. Control variables are year of entry and canton of residence prior to institutionalization. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at municipal level.

Table 1.A.3: Non-parametric Regression Discontinuity Design with other dependent variables

Variable	Conventional (1)	Bias-corrected (2)	Robust (3)
		Residing at home	
French border (β_1)	-.075***	-.065***	-.065***
	(.02)	(.02)	(.02)
Observations on the left	5,149	5,149	5,149
Observations on the right	4,595	4,595	4,595
Bandwidth	17.25	17.25	17.25
Mean of dependent variable	.43	.43	.43
Std. dev. of dependent variable	.50	.50	.50
		Age at entry	
French border (β_1)	.591	.728	.728
	(.50)	(.50)	(.62)
Observations on the left	4,519	4,519	4,519
Observations on the right	4,276	4,276	4,276
Bandwidth	13.87	13.87	13.87
Mean of dependent variable	83.80	83.80	83.80
Std. dev. of dependent variable	8.05	8.05	8.05
Canton fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes - All the estimates are based on individual level data from the three bilingual French and German speaking cantons of Berne, Fribourg and Valais for the period 2007-2013. The dependent variable *Residing at home* is a dummy variable equal to 1 if the elderly person was residing at home prior to institutionalization, and 0 if he/she entered the nursing home from a hospital or from another institution. The dependent variable *Age at entry* is a discrete variable from 50 onwards. The assignment variable is the kilometric travel distance from the closest French speaking municipality on the linguistic border. Controls include year of entry and canton of residence prior to institutionalization. Estimates are performed using the Stata command *rdrobust*. Observations refer to the number of individuals. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at municipal level.

Table 1.A.4: Regression Discontinuity Design with additional controls (non-parametric and parametric)

Column	(1)	(2)	(3)	(4)	(5)	(6)
			Non-parametric RDD (Conventional)			
French border (β_1)	.092**	.109***	.113***	.110***	.104***	.098***
	(.04)	(.04)	(.04)	(.04)	(.04)	(.04)
Observations on the East	5,400	5,309	5,461	5,433	5,433	5,400
Observations on the West	5,868	5,030	5,951	5,899	5,933	5,868
Bandwidth	20.06	18.17	20.73	20.40	20.58	20.14
Mean of dependent variable	2.34	2.32	2.34	2.34	2.34	2.34
Std. dev. of dependent variable	1.02	1.02	1.02	1.02	1.02	1.02
			Parametric RDD (25-km bandwidth)			
French border (β_1)	.121***	.124***	.127***	.121**	.123***	.120***
	(.04)	(.05)	(.05)	(.05)	(.05)	(.04)
Observations	12,780	12,780	12,780	12,780	12,780	12,780
Mean of dependent variable	2.33	2.33	2.33	2.33	2.33	2.33
Std. dev. of dependent variable	1.02	1.02	1.02	1.02	1.02	1.02
Canton fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Immigration rate	Yes	No	No	No	No	Yes
Birth rate	No	Yes	No	No	No	Yes
Gender	No	No	Yes	No	No	Yes
Municipal altitude	No	No	No	Yes	No	Yes
Religion	No	No	No	No	Yes	Yes

Notes - All the estimates are based on individual level data from the three bilingual French and German speaking cantons of Berne, Fribourg and Valais for the period 2007-2013. The dependent variable *Dependency level at entry* is measured on a 0-4 scale. The assignment variable is the kilometric travel distance from the closest French speaking municipality on the linguistic border. Controls include year of entry, canton of residence prior to institutionalization, and some additional controls according to the specification adopted. The additional controls included are the municipal immigration rate, *Immigration rate*, birth rate, *Birth rate*, altitude, *Municipal altitude*, share of catholics, *Religion*, and/or a dummy variable for gender equal to 1 for males, *Gender*. The upper part of the table reports the conventional non-parametric RDD estimates computed with the Stata command *rdrobust*. The bottom part of the table reports the parametric RDD esitmates adopting a 25-km bandwidth and a linear polynomial specification. Observations refer to the number of individuals. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at municipal level.

Table 1.A.5: Estimated Latin language effects on contacts with children and relatives (logit regressions, only individuals aged 60+)

	No. of contacts with children		*No. of contacts with relatives*	
Column	(1)	(2)	(3)	(4)
At least once a week	.013	-.007	.143***	.066***
	(.01)	(.02)	(.02)	(.02)
At least twice a week	.105***	.156***	.062***	
	(.02)	(.03)	(.02)	(.02)
At least three times a week	.146***	.052**	.106***	.047***
	(.02)	(.03)	(.02)	(.02)
Observations	2,632	2,632	3,077	3,077
Demographic controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Canton fixed effects	No	Yes	No	Yes

Notes - Data are drawn from waves 1 to 12 of the Swiss Household Panel (SHP), a yearly panel study administered by the Swiss Federal Statistical Office. More information on this dataset is available at: http://forscenter.ch/en/our-surveys/swiss-household-panel/documentationfaq-2/. This table shows the coefficients of a Latin language dummy variable (equal to 1 if the individual speaks either French, Italian or Romansh or 0 if he/she speaks German) on the probability of having contacts with children (Columns 1 and 2) or relatives (Columns 3 and 4) at least once, twice, or three times a week. Particularly, the SHP relevant variables to compute the number of contacts are "P$$N08 - How frequent are your contacts with children? (times per month)" and "P$$N13 - How frequent are your contacts with relatives? (times per month)". The reported coefficients are the marginal effects of logistic regressions. Demographic variables include sex and age. Observations only include individuals aged 60+ residing in the cantons of Berne, Fribourg and Valais. Standard errors (in parenthesis) are robust to heteroskedasticity.
Source: Swiss Household Panel - years 1999-2010.

Chapter 2

What drives the substitutability between native and foreign workers? Evidence about the role of language

2.1 Introduction

There is an extensive literature about the impact of migrant workers on native wages and employment opportunities.[1] A key element of the discussion is the degree of substitutability between foreign and native workers. On the one hand, if foreign workers are perfect substitutes for native workers, migration inflows should negatively affect native wages because they simply increase the labor force of the destination country (Borjas, 2003; Borjas and Katz, 2007). On the other hand, if foreign workers are imperfect substitutes for native workers, they might specialize in different occupations and improve the efficiency of the labor market, with little effect on native wages. In the classic nested-cell approach derived by Borjas (2003), the national labor force is subdivided into education-experience cells. Migration is treated as a pure supply shock and the different stock of migrants by cell provides the necessary variation to identify the impact of an increase in labor supply on native wages.[2] Ottaviano and Peri (2012) and Manacorda et al. (2012) further extend this model to account for the imperfect substitutability in production of native and foreign workers within the same education-experience group. They find evidence of imperfect substitutability and argue that native and immigrant workers with similar observable characteristics (i.e., education and experience) may still have different comparative advantages in the labor market.

One potential determinant of the imperfect substitutability between foreign and native workers may be the proficiency in the language spoken in the destination country. As shown by Peri and

[1] See Dustmann et al. (2016) and Peri (2016) for a critical review of the literature.

[2] Within this framework, the impact of migration on productivity is neglected. As a result, this analysis may not account for part of the positive effect of migration on the wages of native workers.

Sparber (2009), new migration inflows induce native workers to move from physically demanding jobs to more communicatively intensive jobs. Intuitively, this job specialization process of natives and foreigners in manual and language intensive tasks may be driven by differences in the language proficiency of these two groups of workers and indeed, low levels of language proficiency are associated with worse wage trajectories for migrants (see Dustmann and Fabbri, 2003 and Chiswick and Miller, 2014 for a review). Nevertheless, there might be several other unobservable characteristics (e.g., preferences or willingness to work in manual jobs) that could make immigrants and natives somewhat complementary in the production function.

In this paper, we exploit the peculiarity of the Swiss labor market to shed light on the role of language in driving the imperfect substitutability between native and foreign workers. Switzerland is a multi-lingual country with four official languages spoken, three of which in common with bordering countries (German, French and Italian). Starting from the '50s Switzerland experienced several immigration waves from different countries and even today its foreign-born population is one of the largest among OECD countries (about 27% of working age population). Thus, we observe both immigrants coming from countries sharing the same official language as the native population, and immigrants coming from countries with a different official language. To the same extent, since Swiss linguistic areas are geographically well-delimited, Swiss nationals that moved to other linguistic areas share the same nationality as natives but not the same language. This provides the necessary variation for our identification strategy.

Our empirical analysis extends the nested-cell labor demand model developed by Ottaviano and Peri (2012, OP henceforth) to account for the role played by language. In particular, we first replicate the OP model (Model A) to estimate the elasticities of substitution between foreign and native workers. In replicating their model, we find evidence of imperfect substitutability between native and foreign workers. Then, we compare this elasticity with two alternative models encompassing workers' main language. In Model B, we assume ex-ante perfect substitutability between natives and foreigners with the same linguistic background and we group them together as opposed to foreign workers with different linguistic background. As expected, we find stronger imperfect substitutability between these two groups of workers as compared to the original OP model. In Model C, we add the linguistic background as an additional worker's characteristic to education and experience. After explicitly accounting for the linguistic background, the substitutability between nationality groups increases substantially, and perfect substitutability between foreign and native workers cannot be rejected. These results are quite robust to several robustness checks, such as the inclusion of cross-border workers and different specifications of the model (e.g., cell structure). Despite most of the variation in the years under investigation comes from the large inflow of highly and middle educated workers encouraged by the bilateral agreements on the free movement of people between Switzerland and the EU, we show that our results are not driven by some specific education or nationality group.

Interestingly, once we test whether natives and foreigners specialize in different jobs, we find evidence of native specialization in communicatively intensive jobs in model A, i.e. without controlling for linguistic background. By contrast, if we do control for linguistic background (model C), the job specialization between foreign and native workers substantially decreases. In the most demanding specification, the difference in coefficients between the two models is significant at 5%. This suggests that the imperfect substitutability found in model A is indeed driven by different comparative advantages between foreigners and natives and that the natives' comparative advantage in more communicatively intensive tasks is driven by superior linguistic skills.

In the last part of the paper, we simulate the total wage effects of new migration inflows for the period 1999–2017 focusing on model C, which better models workers' skill mix. In the long run, with full capital adjustment, the overall effect of immigration on wages is, by construction, zero. Nevertheless, considering the wage impact of immigration by education group we find that highly educated workers comparatively experience the most adverse impact of immigration, probably because of the large inflow of highly educated workers in the period considered. Also, we compute short run wage effects on native and foreign workers' wages subdividing the time span of our dataset into three sub-periods corresponding to migration policy changes or to changes in economic conditions. We find that the short run yearly negative impact of migration inflows on native wages increases after the enactment of the bilateral agreements with the EU on the free movement of persons in 2002, and then mitigates after the beginning of the economic crisis in 2009. Furthermore, highly educated workers bear the most adverse consequences of migration, with a yearly decrease in wages after the enactment of the bilateral agreements of 0.9% for natives and 1.6% for foreigners. Again, this can be explained by the upsurge in highly educated foreign workers that moved to Switzerland after the enactment of the bilateral agreements, especially from Germany.

Differently from previous literature, we can directly identify the role of language as the channel through which immigration impacts the labor market of the destination country. To our knowledge, the only other paper investigating this issue is Lewis (2013). Using data from the US, he finds that immigrants with better language skills exhibit greater substitutability for native workers than immigrants with poor language skills. However, immigrants' language skills in the US are likely to be correlated with several other confounding factors because English represents a foreign language for most immigrants who arrive in the US. Conversely, in our setting the selection concerns are mitigated by the fact that we exploit the variation in the mother tongue of both immigrants and natives.

Other papers have exploited the Swiss context to infer the impact of immigration on native wages but none of them investigate the role of language in determining labor market outcomes. For instance, Gerfin and Kaiser (2010) replicate the OP model in Switzerland without controlling for the linguistic background.[3] It is also worth mentioning Beerli and Peri (2015), who exploit the labor market liberalization of cross-border workers between 1999 and 2007 to infer the impact of a large inflow of foreign workers on wages and employment opportunities. Differently from us, they find a positive effect on the wages of highly educated workers and on the working hours of less educated workers. The different results should be due to the large differences in the identification strategies adopted. Indeed, while they exploit a policy instrument that only involved cross-border workers at local labor market level, we evaluate the impact of overall migration flows at national level. Thus, on the one hand, the wage effects computed in this paper should be better able to capture the overall effects of immigration, considering all types of migrants (recent and non-recent) with respect to the counterfactual of no immigration. On the other hand, their identification strategy is more targeted to a specific policy change and is better able to capture the different facets of a labor market liberalization.

The rest of this paper is organized as follows. The next section describes the Swiss context. Then, Section 2.3 presents our theoretical framework and Section 2.4 discusses the data. The empirical specification adopted and the identification issues are discussed in Section 2.5. Section 2.6 presents the estimates of the elasticities of substitution, as well as some evidence about the role of language in determining the specialization of natives in communicatively intensive jobs and the simulated total wage effects of an inflow of foreign workers. Finally, Section 2.7 concludes.

2.2 Background

With an immigrant share of about 27% of the working age population—one of the highest rates among the OECD countries (Liebig et al., 2012)—and 4 official languages spoken in different linguistic areas, Switzerland represents the ideal setting to study the impact of immigrant language skills on labor market outcomes. The four languages spoken are German, French, Italian, and Romansh, which are respectively spoken in the Central and Eastern part, the West, the South, and some specific valleys in the South-East (Figure 2.1). All languages except Romansh, which is spoken by only 0.8% of the population, are in common with bordering countries.

Starting from the post-WWII period, Switzerland also experienced several immigration waves.

[3] Even though they consider a different time span (1991–2008), their results are qualitatively similar to the ones we obtain replicating of the OP model (Model A).

The first immigration wave in the post-war period mainly involved Italians. Then, during the '60s, new sending countries emerged: Germany, France, Austria and Spain. In the '80s a new inflow of workers arrived from Spain, Portugal, Turkey and former Yugoslavia. The inflow of ex-Yugoslavians became particularly pronounced during the 90s, because of the Balkan wars. Finally, with the enactment of the bilateral agreements with the EU on the free movement of persons in 2002, Switzerland experienced a new wave of immigration from European countries, especially from Germany (Liebig et al., 2012).

The bilateral agreements on the free movement of persons deserve particular attention. The free movement of persons for the EU-15 and EFTA countries was first approved in 1999.[4] They allowed citizens of EU-15/EFTA member states to live and work in Switzerland with the only requirement of being employed or financially independent. Moreover, they introduced the harmonization of social security systems, the mutual recognition of professional qualifications and the right to buy properties. In 2002 the free movement of persons for EU-15/EFTA citizens started phasing in, and in 2007 the labor market barriers to workers from these countries were completely removed. After the enlargement of the European Union to Eastern European countries, in 2006 the free movement of persons for the so-called EU-8 member states started phasing in too.[5] Labor market barriers for EU-8 citizens were completely removed in 2011. Finally, in 2009 the labor market integration process started phasing in for Romania and Bulgaria. Labor market barriers for these countries were entirely removed in 2016.

2.3 Theoretical framework

The idea behind the model proposed by OP and by prevalent models in the literature (see for instance, Card, 2001, Borjas, 2003, Card, 2009, and Manacorda et al., 2012) is that each worker is a perfect substitute for other workers with similar skills, but is an imperfect substitute for workers with different skills. However, while some of the previous literature assume ex-ante perfect substitutability between native and foreign workers with the same skill mix (i.e. Borjas, 2003), the model adopted by OP allow for some imperfect substitutability between them. Thus, to investigate the role of language in driving this imperfect substitutability, we modify the OP model. This section provides a simple sketch of their theoretical framework. The interested reader should refer to OP and Borjas (2003) for further details.

[4]EU-15 member states are Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden. EFTA member states are Iceland, Liechtenstein, Norway.

[5]EU-8 member states are Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia.

2.3.1 Theoretical model

Formally, let us assume that the economy follows a Cobb-Douglas production function:

$$Y_t = A_t L_t^{\alpha} K_t^{1-\alpha} \tag{2.1}$$

where output Y_t is produced combining the CES-type labor aggregate L_t and the capital aggregate K_t. A_t is total factor productivity, while α is the share of income going to labor. The subscript t indicates the time at which each of these aggregates is measured. Within a Solow model framework (Solow, 1956), the Cobb-Douglas production function predicts a constant capital-output ratio and a constant detrended capital-labor ratio in the long run, because capital readjusts to short term shocks in labor supply. Thus, in the long run the aggregate wage does not depend on the amount of labor supply and, consequently, the impact of immigration on wages is 0.

Now, to model the different skill mix of native and immigrant workers, we need to partition the original labor aggregate L_t according to relevant workers' characteristics. As an example, workers with different education levels are not competing for the same jobs on the labor market and may be poor substitutes for each other. Thus, workers in the overall labor aggregate L_t can be first partitioned into subgroups according to their education attainment. However, workers within the same education group may still not be perfect substitutes among each other. Indeed, more experienced workers may have different skills than less experienced workers. Thus, education labor aggregates can be further partitioned according to experience on the labor market. Iterating this procedure, the original labor aggregate L_t in Equation (2.1) is subsequently partitioned into more and more characteristics according to a nested structure. Within each characteristic, the imperfect substitutability of workers in different subgroups is modelled through a CES production function. Notice that workers' characteristics are ranked according to an increasing degree of substitutability. In this way, workers within the same labor aggregate are more and more homogeneous as we partition the labor aggregate in an increasing number of characteristics.

Turning to the model, we number each characteristic with $i = 1, ..., I$. Then, the M_i groups within each characteristic are numbered with $g(1) = 1, ..., M_1$ for the first characteristic, $g(2) = 1, ..., M_2$ for the second characteristic, etc. As a result, each labor aggregate up to characteristic $I - 1$ can be written as:

$$L_{g(i)t} = \left[\sum_{g(i+1) \in g(i)} \theta_{g(i+1)} \left(L_{g(i+1)t} \right)^{\frac{\sigma_{i+1}-1}{\sigma_{i+1}}} \right]^{\frac{\sigma_{i+1}}{\sigma_{i+1}-1}} \tag{2.2}$$

where $\theta_{g(i+1)}$ are group specific productivity and σ_{i+1} is the elasticity of substitution between labor aggregates $L_{g(i+1)t}$. Group specific productivity are normalized such that $\sum_{g(i+1) \in g(i)} \theta_{g(i+1)} = 1$.

The nesting order of characteristics implies that $\sigma_{i+1} > \sigma_i$.

Differentiating the production function with respect to each labor aggregate and equating it to its marginal productivity we find the optimality condition for each group g within characteristic i. As an example, the optimality condition for group g and characteristic I is:

$$\begin{aligned}\ln(\omega_{g(I)t}) =& \ln\left[\alpha A \kappa_t^{(1-\alpha)}\right] + \frac{1}{\sigma_1}\ln(L_t) + \\ &\sum_{i=1}^{I}\ln(\theta_{g(i)}) - \sum_{i=1}^{I-1}\left(\frac{1}{\sigma_i} - \frac{1}{\sigma_{i+1}}\right)\ln(L_{g(i)t}) - \frac{1}{\sigma_I}\ln(L_{g(I)t})\end{aligned} \tag{2.3}$$

where $\omega_{g(I)t}$ is the wage paid to workers in group $g(I)$ at time t. κ_t is the capital-labor ratio and σ_1 is the elasticity of substitution between groups of the first characteristic. $\theta_{g(i)}$ are group specific productivity, σ_i indexes the elasticities of substitution for characteristics i and $L_{g(i)t}$ are the labor aggregates corresponding to groups $g(i)$ at time t.

2.3.2 Nesting structure

Figure 2.2 provides a sketch of the nesting structure of the models we are estimating. As previously mentioned, model A replicates the OP model, where workers are subdivided according to three characteristics: education, experience and nationality. However, we adopt different groupings of workers within each characteristic to better tailor the model to the Swiss labor market and education system and, at the same time, limiting the number of cells to guarantee a sufficient number of individuals in each cell. Specifically, we partition labor aggregates according to three education groups (low, medium and high), two experience groups (young and old), and two nationality groups (natives and foreigners). Further details on group construction are provided in the next section.

To investigate the role of language in driving the substitutability between native and foreign workers, in models B and C we modify this structure. If language plays a role, foreigners with different linguistic background should be less substitutable with respect to native workers than foreigners with the same linguistic background. Thus, in model B we assume ex-ante perfect substitutability between foreigners with the same linguistic background and natives and we group them together in the definition of nationality groups, as opposed to foreign workers with a different linguistic background. Then, we attempt to control directly for the linguistic background of native and foreign workers considering the linguistic background as an additional characteristic of the workers' skill mix. As a result, in model C we further partition the labor aggregates according to the linguistic background, assuming that workers within the same linguistic background but with different nationalities are more substitutable than workers with the same nationality but a different linguistic background. Even though this assumption may be reasonable, we also test for the other possibility, i.e. that workers with the same nationality but a different linguistic background are more substitutable than workers with a different nationality and the same linguistic background.

2.4 Data and descriptive statistics

In this section we discuss the major data issues, while the details are left to Appendix 2.B. Data are drawn from the Swiss Labor Force Survey (SLFS) for the period 1999–2017. We restrict the dataset to people aged 18 or above with active working status and remunerated work in the previous week. We also drop individuals in military service or in education. Our sample size prior to collapsing by cell consists of 446,304 observations. Given the large number of cells (228 year-education-experience-nationality cells in model A and B and 456 year-education-experience-linguistic background-nationality cells in model C) we prefer to report the main estimates without further partitioning by gender, since this would further reduce the precision of the estimates. Separate results for men and women are available in Appendix 2.C.

We also exploit the information contained in the O*NET database to understand whether workers with different linguistic backgrounds specialize in different occupations. O*NET is a database developed for the US containing a detailed description of the skills required by each type of job. Particularly, for every occupation a score between 0 and 100 is assigned to each skill, according to experts' judgement. This score corresponds to the importance of that skill to perform the job. Following Peri and Sparber (2009), we derive a measure of the communication content of each occupation averaging the importance scores of four basic communication skills (Oral and Written Comprehension, Oral and Written Expression). To the same extent, we define an extended measure of communication skills adding cognitive, analytical and vocal skills to the four basic skills listed above. More details on the construction of these measures are available in Appendix 2.B.

Given the structure of the Swiss education system, we subdivide workers according to three education groups. In the first group we include workers that only completed compulsory education or basic vocational training. In the second group we include workers with full vocational training, high school diploma, or tertiary vocational training. Finally, in the third group we include workers with college education.

Then, we subdivide individuals according to their potential experience in the labor market. Potential experience is computed as the difference between current age and the age at which individuals should have completed education.[6] While OP adopt a specification with 8 experience

[6]We assume that people with compulsory education entered in the labor market at age 14, people with basic vocational training entered at age 16, people with apprenticeship or full time vocational training at age 18, people with high school diploma at age 19, people with tertiary vocational training at age 22 and people with college education at age 24.

groups (5-year intervals), in the present context partitioning workers into such a large number of experience groups leads to implausible high estimates of the elasticity of substitution, suggesting almost no role for experience. Indeed, narrow experience groups may decrease the number of observations per cell too much, increasing the noise and the substitutability across groups. To overcome this issue and obtain elasticities of substitution in line with the previous literature, we only use two broad experience groups (as in Katz and Murphy, 1992). Specifically, we define workers with up to 15 years of experience (first tercile of the experience distribution) as “young” and workers with more than 15 years of experience as “old”. People with zero or more than 40 years of experience are left out of the sample. Further discussion on this issue and some sensitivity analysis are provided in Section 2.6.3.

Nationality cells are defined according to citizenship. People with Swiss citizenship are defined as Swiss, while people with non-Swiss citizenship are defined as non-Swiss.[7]

Finally, linguistic background cells are defined according to the main language spoken by the individual. The main language spoken by Swiss citizens is inferred by the language in which the questionnaire has been completed. The languages available to complete the questionnaire are German, French and Italian. For simplicity, we drop individuals living in Romansh speaking areas from the sample (around 1,000 individuals out of 446,000). Swiss citizens that decide to complete the questionnaire in a different language from the main language spoken in the area of residence are counted as “different linguistic background”. They are counted as “same linguistic background” otherwise. To the same extent, the main language spoken by foreigners is inferred from the official languages of their country of citizenship and foreigners are assigned to linguistic background cells accordingly. The specific nationalities included in each linguistic background group are listed in Appendix 2.B.4.

Labor aggregates are constructed according to the number of hours actually provided the week before. We drop from the sample individuals with missing values or zero hours worked. Then, we multiply the hours worked by each individual by his personal weight (provided by the SLFS) and we sum up the number of weighted hours by cell.

To compute the average weekly wage by cell we divide annual net income by 52 and we drop observations with income equal to zero.[8] Also, we trim 1% of the observations at the top and at the bottom of the income distribution. Then, we obtain real wages adjusting nominal wages according to the price consumer index. Finally, we average wages by cell weighting each observation by the number of hours worked times the personal weight.[9]

[7]Swiss citizens with double citizenship are considered as Swiss. More details are provided in the Appendix 2.B.3.

[8]In the SLFS there is no information about the number of weeks worked in a year.

[9]Since in Switzerland part-time jobs are widespread, differently from OP we do not restrict the sample to full-time

2.4.1 Descriptive statistics

Table 2.1 lists the 5 most represented nationalities among immigrants with the same linguistic background and immigrants with different linguistic background in the SLFS. It is worth noting that Italian immigrants appear in both groups. They represent the largest group among immigrants with a different linguistic background (especially in the German speaking part of Switzerland), but also the largest immigrant group in the Italian speaking region.

Table 2.2 shows the percentage variation in native wages and in hours worked by foreign workers between 1999 and 2017 by education, experience and linguistic background group. In the period considered, the percentage increase in hours worked by foreign workers is particularly pronounced among the highly educated, while it is negative among the low educated. This is in line with the findings of Beerli and Peri (2015) and Beerli and Indergand (2015), that find evidence of a shift in labor demand towards highly educated workers. By contrast, native workers experienced negative real wage growth for almost all groups.

Finally, Table 2.3 provides the average scores for communication skills by education group. As expected, workers with the same linguistic background perform jobs with a higher communication content with respect to workers with a different linguistic background and highly educated workers perform jobs with a higher communication content with respect to low educated workers. These results are consistent across nationality groups. This suggests that even though natives that decide to move to other linguistic areas may have a superior knowledge of the language of destination than non-movers, there are still differences in the linguistic content of their jobs with respect to local natives. Indeed, a mean comparison test between natives and foreigners with same and different linguistic background always rejects the null of equal means in the communication content of jobs (except for middle educated native workers).[10] Table 2.C.1 provides the same information for the extended definition of communication skills.

2.5 Estimation and identification

We begin by estimating the elasticities of substitution between nationality groups. The empirical specification to be estimated can be obtained taking the ratio between the optimality conditions in Equation (2.3) for foreigners and natives. Particularly, we regress the ratio between the average wages of Swiss and foreign workers against the ratio of total hours supplied by the two groups.

workers. Indeed, restricting the sample to people working 30 hours per week or more reduces our sample size by 25%. However, the weighting procedure of wages should account for differences in hours supplied.

[10] We perform two different types of mean comparison tests. The first one is unconditional, while in the second one we also control for sex, experience, and education. Also, controlling for the European origin of foreign workers does not change the test results. In all the regressions, observations are weighted by hours worked times personal weight.

Formally, we estimate the following equation:

$$\ln\left(\frac{\omega_{rFt}}{\omega_{rNt}}\right) = \psi_r + \lambda_t + \beta_{nat}\ln\left(\frac{L_{rFt}}{L_{rNt}}\right) + \varepsilon_{rt} \tag{2.4}$$

where r indicates the generic labor aggregate partitioning up to nationality. The coefficient β_{nat} is the inverse of the elasticity of substitution between nationality groups (i.e., $\beta_{nat} = 1/\sigma_{nat}$). This implies that the smaller the coefficient, the larger the elasticity of substitution, i.e. the substitutability between workers. ψ_r is a group fixed effect and corresponds to the ratio between nationality fixed effects (i.e., $\psi_r = \ln(\theta_{rF}/\theta_{rN})$). Group fixed effects should capture the differences in productivity between different education-experience-linguistic background combinations. λ_t accounts for time fixed effects and ε_{rt} is a stochastic component independent of $\ln(L_{rFt}/L_{rNt})$. To account for the differences in the number of workers with specific characteristics, all the regressions are weighted by the share of foreign workers to native workers by cell.[11] If fixed effects are correctly specified, the error term is independent of the labor aggregates, since all the endogeneity should be absorbed by group and time specific fixed effects.[12] If this assumption holds, immigration can be regarded as an exogenous shock allowing for the identification of the beta parameter (and thus, of the elasticity of substitution between nationality groups). Since group specific productivies sum up to 1, they can be retrieved from the definition of ψ_r through the formulas $\theta_{rF} = \frac{\exp(\psi_r)}{1+\exp(\psi_r)}$ and $\theta_{rN} = \frac{1}{1+\exp(\psi_r)}$.

Now, we can retrieve the labor aggregate L_{rt} from Equation (2.2). In this way, in constructing the labor aggregates of less substitutable characteristics we account for the imperfect substitutability between workers of different nationalities. The average wages, instead, can be computed averaging the wages of different nationality groups by the share of labor provided by that group, i.e.:

$$\bar{\omega}_{rt} = \omega_{rFt}\left(\frac{L_{rFt}}{L_{rt}}\right) + \omega_{rNt}\left(\frac{L_{rNt}}{L_{rt}}\right) \tag{2.5}$$

From now on, to estimate the elasticities of substitution between upper level characteristics it is possible to revert to the original Borjas approach and use the hours worked by migrant workers as a supply shock to instrument the overall hours worked in each education-experience-linguistic background cell. Indeed, hours of labor provided by natives may be endogenous to wages. However, if fixed effects are correctly specified migration should be mainly driven by demographic factors and the variation in the amount of labor provided by foreign workers across cells can be used to identify

[11] Indeed, the number of workers may differ across cells, influencing both labor aggregates and average wages. Weighting the regressions for the number of workers in each cell should account for this.

[12] Note that taking the ratio between the optimality conditions in Equation (2.3) it would be sufficient to control for group fixed effects ψ_r, since all the other terms are washed out. As noted by OP, since we use ratios of wages and labor supply within groups, any variation of group specific productivity would cancel out. However, in our baseline econometric specification we prefer to include time fixed effects as well, to account for possible year-specific differential trends in wages between nationality groups.

the impact of an increase in labor supply on wages.[13] Thus, we proceed to the 2SLS estimation of the other characteristic's elasticities of substitution exploiting the optimality condition in Equation (2.3) and instrumenting the labor aggregate L_{rt} with immigrant labor supply L_{rFt}. Again, the estimated coefficients are the inverse of the elasticities of substitution (i.e. $\beta_i = 1/\sigma_i$). This procedure is iterated up to the estimation of the elasticity of substitution across education labor aggregates.[14]

2.5.1 Total wage effect

The main advantage of a nested CES framework consists in the possibility to derive the total wage effect of immigration. The reduced form approach usually focuses only on a partial wage effect, i.e. the impact of foreign workers on the wage of native workers within the same education and experience group. However, an inflow of foreign workers also affects workers in different cells, because of the imperfect substitutability between workers with different skill mix. The nested CES structure accounts for these additional wage effects across cells, overcoming the major flaw of a reduced form approach. Particularly, let $s^i_{g(I)}$ denote the share of labor income of workers of type $g(I)$ sharing the same characteristics up to i. Then, from Equation (2.3) we can derive the percentage variation in wages of another group of workers $h(I)$ due to an inflow of workers in group $g(I)$.[15] Assuming that workers of type $g(I)$ and workers of type $h(I)$ share the same characteristics up to characteristic c, the percentage wage change for workers $h(I)$ can be written as:

$$\frac{\Delta\omega^0_{h(I)}/\omega^0_{h(I)}}{\Delta L_{g(I)}/L_{g(I)}} = \frac{s^0_{g(I)}}{\sigma_1} > 0, \qquad c = 0 \tag{2.6}$$

and

$$\frac{\Delta\omega^c_{h(I)}/\omega^c_{h(I)}}{\Delta L_{g(I)}/L_{g(I)}} = -\sum_{i=0}^{c-1} \frac{s^{i+1}_{g(I)} - s^i_{g(I)}}{\sigma_{i+1}} < 0, \qquad c = 1, ..., I \tag{2.7}$$

Equation (2.6) implies that an inflow of workers in group $g(I)$ has a positive impact on the wages of workers in group $h(I)$ if the workers of the two groups do not share the first characteristic. In

[13]This approach is quite standard in the literature on the impact of migration at national level. As noted by Borjas (2003), if demographic factors are not the sole drivers of migration, higher wages should trigger higher migration inflows, inducing a positive correlation between hours worked and wages. If this is the case, the estimated coefficients should be biased towards 0, and the estimates of the elasticities of substitution provide an upper bound of the true elasticities of substitution.

[14]Note that controlling for the correct specification of fixed effects is extremely important for the estimation of upper level coefficients, since all the terms in Equation (2.3) that washed out taking the ratio between nationality groups do not vanish anymore. Thus, including time fixed effects becomes now very important to account for the group-invariant terms of Equation (2.3) (i.e. $\ln[\alpha A\kappa_t^{(1-\alpha)}] + \frac{1}{\sigma_{edu}}\ln(L_t)$). In addition, group fixed effects account for the time-invariant terms (i.e. $\sum_{i=1}^{I}\ln(\theta_{g(i)})$). The fixed effects controlling for the other terms in Equation (2.3) (i.e. $\sum_{i=1}^{I-1}\left(\frac{1}{\sigma_i} - \frac{1}{\sigma_{i+1}}\right)\ln(L_{g(i)t})$), depend on the structure of the model chosen and are further discussed in Section 2.6.

[15]The interested reader can find the proof in OP.

contrast, if groups $g(I)$ and $h(I)$ share at least one characteristic, an inflow of workers in group $g(I)$ depresses the wages of workers in group $h(I)$. This effect is stronger the larger the number of characteristics the two groups have in common.

To assess the total wage effect of immigration, we perform a simulation. Particularly, for each estimated elasticity parameter we take 5,000 random draws from a joint normal distribution and we compute the percentage wage change induced by the percentage increase in foreign workers in the period considered combining these simulated values with the labor income shares of each group of workers. Then, we average these percentage wage changes across random draws to obtain the average wage effect and the standard deviation for each experience-education-linguistic background group. Finally, average wage effects and standard errors are aggregated at higher levels using the appropriate wage shares. A detailed description of the method adopted is provided in Appendix 2.A.

Long run and short run wage effects

An inflow of foreign workers may divert the capital-labor ratio from its long run trend. In the standard Solow (1956) model the capital-labor ratio is assumed to grow at a positive constant rate. However, immigration inflows decrease the capital-labor ratio, causing the marginal productivity of capital to increase. In the long run, the greater investments in capital will bring the capital-labor ratio back to its original growth path. Thus, the aggregate impact of labor inflows on wages is zero in the long run because of capital readjustment. However, in the short run there could be some negative effects due to a sluggish capital response to labor inflows. In our simulation we present two alternative scenarios. The first scenario shows the long run effects of immigration, assuming full readjustment of capital. The second scenario shows the effects in the very short run, assuming fixed capital. Since immigration is not an unpredictable shock in time and investors continuously respond to labor inflows, this latter assumption may be too strict. However, the simulated wage effects in the second scenario may be considered as lower bounds of the true wage impact of immigration. Greater details are provided in Appendix 2.A.

2.5.2 Identification issues

One major concern about the empirical strategy may involve the area of origin of foreign workers. If foreign-born workers in different education or linguistic background groups are very different from each other, the elasticities of substitution we are estimating may be driven by nationality effects. For instance, foreign workers coming from Western Europe may be clustered in some specific linguistic background-education groups (e.g., same language and high education), while people coming from other countries may be clustered in other groups. Reassuringly, the upper panel in Figure 2.3

shows the common support in the area of origin by education group. Each bar represents the share of migrants from a different area of origin: Western Europe, Eastern Europe, Africa and other nationalities.[16] All the areas of origin are well represented in all the three education groups, even though the share of workers from Western Europe is slightly larger among the highly educated. To the same extent, the bottom panel in Figure 2.3 represents the distribution of areas of origin by linguistic group. Western European countries are represented in both groups. However, the great majority of migrants with the same linguistic background comes from Western Europe, while Eastern European countries are not represented at all. Nevertheless, as shown in Section 2.6.3, our estimates are robust to the exclusion of Eastern European migrants.[17]

As shown by Dustmann et al. (2013), allocating immigrants into skill cells might represent another possible threat for our identification strategy if immigrants downgrade considerably upon arrival—leading them to be overqualified, at least on paper, for the job they perform. This may happen for a number of reasons, such as the difficult comparability of the educational system in the origin country, the lack of knowledge of the job market in the destination country, lower reservation wages, etc. If this is the case, foreign workers are not directly competing with native workers with their same education attainment, but with native workers with a lower education level. As a result, comparing native and foreign workers within the same education group may be misleading. In the Swiss case, this should be less of a concern since foreign workers mainly come from European countries and, more generally, the entrance in the Swiss labor market is heavily regulated. However, Table 2.4 reports the number and the share of foreign and native workers by occupational category for middle educated workers. Even though foreign workers may be slightly more represented within occupations requiring lower education, the overall distributions of foreign and native workers seem to be quite similar, suggesting that the amount of downgrading of middle educated workers is not worrisome in our context. Table 2.C.2 in the Appendix reports similar evidence for highly educated workers.

Another concern may involve the greater ability of highly educated workers to learn the language of the destination area, or their use of English as working language. Notice that since the elasticity of substitution between nationality groups is an average over different education groups, the greater ability of highly and middle educated workers to learn a new language should bias the estimates towards 0, i.e. towards perfect substitutability. Moreover, this effect should be homogeneous across models B and C and should not affect the main conclusions of the paper. In Section 2.6.3, we provide

[16] Eastern Europe includes all the former Soviet Union countries, ex-Yugoslavia countries and Turkey.

[17] To give an idea of how migrants with same and different linguistic background are distributed across Switzerland, we provide some maps of their distribution at spatial mobility region level (i.e. local labor markets). However, since in the empirical analysis we are not exploiting the variation in the geographical distribution of migrants, but only the variation within different cells, these maps are reported in Appendix (Figure 2.C.1).

an additional robustness check excluding highly educated workers from the sample.

Finally, a serious limitation of the SLFS is the lack of cross-border workers, who represent a non-negligible share of foreign workers. Particularly, in the Swiss labor market there are around 300,000 cross-border workers, representing roughly 8% of total employment and 30% of foreign workers.[18] For this reason, we perform a robustness check complementing the SLFS data with data coming from the Swiss Earning Structure Survey (SESS), a biannual survey administered to approximately 35,000 firms about the earnings of employees in the secondary and tertiary sectors, including cross-border workers. The results are in line with our main findings and are further discussed in Section 2.6.3.

2.6 Results

We begin by estimating the elasticity of substitution between nationality groups for our three models A, B, and C. Table 2.5 presents the estimated coefficients ($\beta_{nat} = 1/\sigma_{nat}$). To correctly interpret the results, recall that in these models an elasticity of substitution σ_{nat} close to ∞ corresponds to perfect substitutability, while smaller values of σ_{nat} reveal the presence of imperfect substitutability. For each model we present three specifications that differ in the fixed effects included. In the first specification we only include group and time fixed effects. Then, in the second specification we add time by education fixed effects. These effects capture possible systematic differences in wage trends across education groups. Finally, following Borjas et al. (2008), in the third specification we also add time by experience fixed effects for models A and B and time by experience and time by linguistic background fixed effects for model C.

In model A, our benchmark model based on OP, the inclusion of time by education fixed effects substantially improves the precision of the estimates, leading to a negative and statistically significant coefficient of -0.081. Adding time by experience fixed effects decreases the magnitude of this coefficient to -0.048. These values correspond to an elasticity of substitution, σ_{nat}, of 12 and 21. The second estimate is in line with the results of OP, who find an elasticity of substitution between native and foreign workers around 20. On the other hand, Manacorda et al. (2012), using data from the UK Labor Force Survey, find an elasticity of substitution between nationality groups around 7. Thus, we can conclude that our results are quite in line with previous literature and that native and foreign workers are fairly imperfect substitutes in the Swiss labor market. As suggested by Peri and Sparber (2009), this imperfect substitutability may be driven by residual differences in the actual skill mix of immigrant and native workers which induce them to specialize in different

[18] The number of cross-border workers is released every year by the Swiss Federal Statistical Office. We compute the incidence of cross-border workers on total employment and foreign workers from SESS data.

occupations. In Section 2.6.1 we explicitly investigate the role of language in determining the specialization of workers in different occupations.

In model B natives and foreigners with the same linguistic background are grouped together as opposed to foreigners with a different linguistic background. If language plays a role in determining the substitutability between native and foreign workers we expect larger coefficients with respect to model A, i.e. lower substitutability between foreigners with a different linguistic background and the other groups of workers. Indeed, the estimated coefficients are larger than those estimated in Model A and range between -0.112 and -0.128. These values correspond to an elasticity of substitution between 8 and 9, pointing towards a non-negligible role of language in determining the imperfect substitutability between nationality groups.

Finally, including the linguistic background as an additional workers' characteristic (model C) the estimated coefficients become essentially zero. In all the specifications, the null hypothesis of a zero coefficient, i.e. perfect substitutability, cannot be rejected. Overall, these results underscore the importance of language in driving the substitutability between foreign and native workers.

After estimating the elasticity of substitution between nationality groups, we can recursively estimate the elasticities of substitution for the other workers' characteristics, i.e. linguistic background, experience and education. These elasticities are reported in the Appendix (Tables 2.C.3–2.C.5). Clearly, the only model in which workers are grouped according to their linguistic background is model C. Controlling for group and time fixed effects (Column (1)) leads to an estimated elasticity of substitution of 15. However, in this model the inclusion of time by education fixed effects leads to a weak instrument problem. Indeed, given the low variation over time in the hours supplied by workers in the middle education group, time by education fixed effects absorb all the variation in the first stage regression. For this reason, we include a third less demanding specification, replacing group fixed effects with education, experience and linguistic background fixed effects and linguistic background by education fixed effects (Column (3)). This allows us to overcome the weak instrument problem and the resulting estimated elasticity ends up to be similar to the elasticity of substitution estimated in Column (1).

Regarding the other workers' characteristics (i.e., experience and education) the estimated elasticities of substitution are consistent with the elasticities of substitution estimated in the literature. It is only worth mentioning that in the case of education we end up with 57 observations. This implies that we do not have sufficient degrees of freedom to include time by education fixed effects.[19] Thus, we only control for education specific time trends. The results imply an elasticity of substitution across education groups which varies between 4 and 6.

[19] In the baseline specification we are also controlling for 19 year fixed effects and 3 education fixed effects.

It is also interesting to look at the degree of imperfect substitutability between linguistic background groups holding workers' nationality fixed. In other words, we invert the order between linguistic background and nationality characteristics in model C. Although this nesting structure is misspecified, this result can still be informative about the determinants of workers' substitutability.[20] Table 2.C.6 in Appendix presents the results. The elasticity of substitution between linguistic background groups is between 7 and 11. Notice that this value is fairly similar to the elasticity of substitution between nationality groups estimated in model A, reinforcing the idea that language plays an essential role in determining the imperfect substitutability between workers, even between workers of the same nationality.

2.6.1 Job specialization

So far we showed the importance of the linguistic background in determining the elasticity of substitution between native and foreign workers. In this section we investigate whether workers with a different linguistic background specialize in different types of jobs. To this end, we focus on the communication skills required by each job and we perform the following regression:

$$\ln\left(\frac{C_{rFt}}{C_{rNt}}\right) = \psi_r + \lambda_t + \beta \ln\left(\frac{L_{rFt}}{L_{rNt}}\right) + \varepsilon_{rt} \tag{2.8}$$

where C_{rFt} and C_{rNt} are respectively the average communication skills required by foreign and native workers' jobs.[21] As before, ψ_r and λ_t are group and time fixed effects, while L_{rFt} and L_{rNt} are the hours of labor provided by foreigners and natives. Note that this is the same regression as in Equation (2.4) but we replace the dependent variable with the ratio between the average communication skills of foreigners' jobs and the average communication skills of natives' jobs. If natives and foreigners specialize in different types of jobs we expect an inflow of foreign workers to decrease the foreign-to-native ratio in communication skills, either increasing the average communication content of natives' jobs or decreasing the communication content of foreigners' jobs. Then, we compare the regression results in model A, that do not account for the linguistic background, with the regression results in model C, that explicitly control for the linguistic background.

The results reported in Table 2.6 uphold our theoretical predictions. As expected, in Model A we find evidence of a significant relationship between immigration and job specialization. In particular, a one standard deviation increase in the relative supply of foreign workers, L_{rFt}/L_{rNt} (that corresponds to a 3.5 percentage points change in the relative supply of foreign workers)

[20] Since the elasticity of substitution between linguistic background groups is smaller than the elasticity of substitution between nationality groups, this model specification is incorrect. In a robust specification of the model, workers' characteristics should be ordered according to increasing degree of substitutability.

[21] Further details on the construction of this variable are provided in Appendix 2.B.8.

decreases the foreign-to-native ratio in communication skills, C_{rFt}/C_{rNt}, of .17 percentage points. In other words, an inflow of foreign workers would either increase the average communication content of natives' jobs or lead immigrants towards more manual occupations.[22]

The differential job specialization between foreign and native workers substantially decreases after controlling for the linguistic background (Model C). Moreover, after accounting for time by experience and time by linguistic background fixed effects, the estimated coefficient in Model C (Column (6)) is statistically different at 5% with respect to the estimated coefficient in Model A (Column (3)). Results adopting the extended definition of communication skills are also consistent (see Table 2.C.7 in Appendix).

2.6.2 Simulated total wage effects

In this section we present the simulated total wage effects of new immigration flows. In doing this, we focus on model C, that better captures the different skill mix of workers. As discussed in Section 2.5.1, we use the estimated elasticities of substitution as key parameters of joint normal distributions and we simulate the wage effects averaging percentage wage changes over 5,000 random draws.[23]

Table 2.7 reports the simulation results. In the first column we report long run estimates for the whole period under investigation, i.e. 1999–2017. Panels A and B of Table 2.7 present the wage effects respectively for native and foreign workers. Each panel reports the overall wage effect and the wage effects by education group. Since new immigrants are assumed to be perfect substitutes for previous immigrants, previous immigrant workers bear the most adverse consequences of immigration. Interestingly, even in the long run, highly educated workers seem to be negatively affected by the migration inflows.

The last three columns of Table 2.7 report short run simulation results for three sub-periods: before the enactment of the bilateral agreements on the free movement of persons (years 1999–2001), between the enactment of the bilateral agreements and the beginning of the economic crisis (years 2002-2008) and after the start of the economic crisis (years 2009-2017). These effects are not directly comparable with the long run estimates in the first column of Table 2.7. However, they represent the lower bound wage impacts of migration inflows within the three sub-periods of interest. Moreover, since these three sub-periods differ in length, it is useful to compare yearly wage effects, computed as the reported coefficients divided by the number of years in the sub-period. The wage impact of immigration flows is largest after the enactment of the bilateral agreements with the

[22]In a separate robustness check, we also ascertain whether the effect comes from a increase in the native-born supply of communication tasks (denominator) or a decrease in the foreign-born supply of the same tasks (numerator). Our results significantly support both channels.

[23]Particularly,we plug into the normal distributions a value of $1/\sigma$ equal to 0.010 for nationality groups, 0.085 for linguistic background groups, 0.185 for experience groups and 0.257 for education groups.

EU (Column 3), especially for highly educated workers. Indeed, between 2002 and 2008 the large inflow of highly educated workers negatively affected the wages of highly educated native workers by 0.9% per year and the wages of highly educated foreign workers by 1.6% per year. We also find some negative effects on low educated workers, but the impact is smaller in magnitude (-0.2% per year for natives and -0.3% per year for foreigners). These effects mitigate in the aftermath of the economic crisis (Column 4).

2.6.3 Robustness checks

Tables 2.C.8–2.C.11 in Appendix present the estimated coefficients separately for men and women. Partitioning the labor aggregate by gender, the precision of the estimates significantly decreases, with larger standard errors with respect to the main estimates, especially for women. The estimated coefficients by gender are generally smaller than the estimated coefficients for the pooled sample in models A and B and have the wrong sign in model C. Moving to upper level characteristics, the elasticities of substitution between groups are often positive for women, suggesting that the cell specification adopted for the pooled sample may not be appropriate for women alone. This could be due to the peculiar structure of the Swiss labor market, where the female participation rate is rather high (about 80% in 2015 according to OECD estimates), but where about 45% of women work part-time (less than 30 hours per week) (OECD, 2016a). For men, the elasticities of substitution between linguistic background, experience and education groups show negative coefficients. However, in many cases the first stage F-statistic is very low, suggesting a weak instrument problem. Moreover, where the F-statistic is particularly low, the estimated elasticities of substitution are also implausibly low. As a result, pooling together men and women is particularly important to increase the predictive power of the instrument and the precision of our estimates.

As already mentioned, we also test the robustness of our estimates to the inclusion of cross-border workers using data from the SESS. Unfortunately, the SESS does not contain data about the language spoken by workers (nor about the nationality of foreign workers) and cannot be used to replicate the empirical analysis of this paper. However, assuming that cross-border workers have the same linguistic background as native workers, we compute the incidence of cross-border workers' wages and hours provided out of foreign population by cell, and we inflate the wage and labor aggregates in the SLFS according to these shares. Since the SESS is a biannual survey, we linearly interpolate the missing years. Given that this imputation procedure may affect the consistency of the results, the estimated coefficients should be interpreted with caution. Table 2.C.12 shows the elasticities of substitution between native and foreign workers. The estimated coefficients are in line with the main results.

Since in these models workers' characteristics are ordered according to an increasing degree of substitutability, we also provide a robustness check inverting the order of experience and linguistic background characteristics in model C. Results are presented in Table 2.C.13. To overcome the weak instrument problem, in Column (4) and (6) we report the estimated coefficients controlling for education, linguistic background and/or experience fixed effects separately rather than controlling for group fixed effects. However, the coefficients for linguistic background groups are smaller in magnitude than the coefficients for experience, suggesting a larger elasticity of substitution between linguistic background groups. Thus, the original specification of model C should be preferred.

Then, we also provide some sensitivity analysis about the definition of experience groups. The upper part of Table 2.C.14 shows the estimated coefficients with 8 experience groups for model A.[24] The estimated elasticities of substitution between different experience groups are implausibly high, as there are no similar results in the literature. Moreover, given the large number of cells and the high substitutability between experience groups, the coefficients for nationality groups are not significant anymore. Thus, we re-estimate the model defining experience groups according to terciles, i.e. three experience cells with the same number of observations. The first tercile corresponds to people with less than 15 years of experience, the second tercile corresponds to people between 15 and 25 years of experience and the third tercile corresponds to people between 26 and 40 years of experience. The bottom part of Table 2.C.14 shows the coefficients estimated adopting this group specification. Again, the coefficients for nationality are not significant and the elasticities of substitution for experience groups are still implausibly high. Thus, since the median workers in the second and the third experience terciles are much similar terms of acquired skills and wages with respect to the median worker in the first tercile, in the main analysis we decide to group together the second and the third terciles.[25]

With respect to education groups, we try to understand how their definition impacts the final results. To do so we first group together middle and highly educated workers. Then, we replicate the analysis grouping together low and middle educated workers. Table 2.C.15 shows the elasticities of substitution between nationality groups in the three models with these different definitions of education groups. Indeed, results grouping middle educated workers together with highly educated workers are very similar to the results in the main specification. On the other hand, grouping middle educated workers together with low educated workers makes all the estimates very imprecise and not significant. This suggests that middle educated workers better substitute highly educated workers than low educated workers. For the sake of conciseness, we do not report the coefficients

[24]Results for models B and C are similar and are not reported.

[25]To define the "young" group we also considered a lower experience threshold (i.e., first quartile). However, the reduction in the number of workers in many cells leads to very imprecise estimates.

for linguistic background, experience or education. However, in both cases these elasticities are much more imprecise, suggesting that the specification with three different education groups is the most appropriate one.

An important concern about this analysis is the fact that foreign workers with the same linguistic background mainly come from Western European countries, while migrants from Eastern Europe always have a different linguistic background. To reassure the reader against this caveat, we perform a robustness check excluding migrants from Eastern Europe from the sample. Notice that this procedure is inconsistent with the theory, since elasticities should always be computed on labor aggregates defined recursively subdividing the overall labor aggregate in the economy. Within this framework, excluding a subgroup of individuals from the sample may induce some mechanical bias in the estimated elasticities. This bias may have different direction according to the wage pattern and the type of workers excluded. However, even adopting this incorrect procedure, elasticity estimates are robust to the exclusion of these workers. Results are presented in Table 2.C.16.

As discussed in Section 2.5.2, we exclude highly educated workers from the sample as further robustness check. The estimates of the elasticities of substitution between nationality groups are reported in Table 2.C.17. As expected, the results are still consistent across the three models, with all the coefficients slightly increasing in magnitude.

Finally, we replicate the analysis constructing labor aggregates using contract hours or employment instead of the actual number of hours worked the week before. Also, we replicate the analysis without weighting the regressions by the number of workers per cell. In both cases, results are qualitatively similar to the main estimates and are not reported.

2.7 Conclusion

This paper investigates the role of language in determining the substitutability between foreign and native workers. The main advantage of the Swiss context is that we can compare the labor market outcomes of natives and foreigners with a different linguistic background. We exploit the linguistic diversity of Switzerland and we modify the model proposed by Ottaviano and Peri (2012) to account for the linguistic background of immigrants and natives.

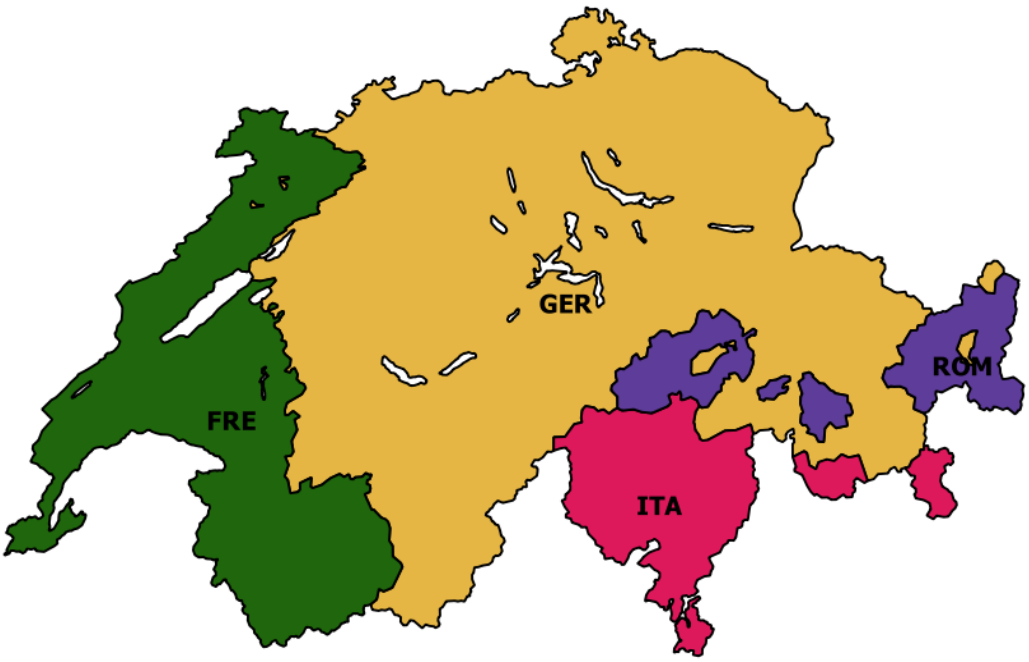
The results confirm the importance of language in determining the substitutability between native and foreign workers. After accounting for the linguistic background, the elasticity of substitution between foreign and native workers dramatically increases, approaching perfect substitutability. Moreover, the native workers' specialization in more communicatively intensive jobs substantially decreases. Overall, immigrant workers sharing the linguistic background of the incumbent population are potentially perfect substitutes for natives, while natives with a different linguistic background are not, as well as foreigners with a different linguistic background.

Finally, we exploit the nested CES structure to compute the total impact of immigration on wages. The wage effects of migration in the long run are small (+0.7% for natives and −3.0% for foreigners) and not significant for natives. In computing short run effects we subdivide the time horizon under consideration in three sub-periods and we simulate the percentage wage changes separately for each of them. We find that highly educated workers experienced some adverse wage effects from the recent migration inflows. This negative effect is larger after the enactment of the bilateral agreements (years 2002–2008) and decreases after the burst of the economic crisis (years 2009–2017).[26] Paradoxically, these results suggest that the inflow of highly educated workers from neighboring countries who share the natives' linguistic background may have reduced the level of wage inequality across education groups, or at least mitigated the labor market trends observed in many developed economies showing an increasing level of wage inequality over time (e.g., Acemoglu and Autor, 2011).

Even though the peculiarity of the Swiss context does not allow for a direct generalization of the results, the main conclusions of this paper can be extended to other high income countries. For instance, foreign workers in the US or in the UK should be less likely to speak English as a mother tongue language with respect to the average migrant in Switzerland. Thus, the differential specialization in more manual intensive tasks for migrant workers is more likely to take place and to be stronger. This is in line with the results by Lewis (2013). To the same extent, if the average migrant is less likely to be skilled than in Switzerland, the differential specialization in more manual intensive tasks is also more likely to be stronger. From the migrant point of view, these results also highlight the importance of linguistic training.

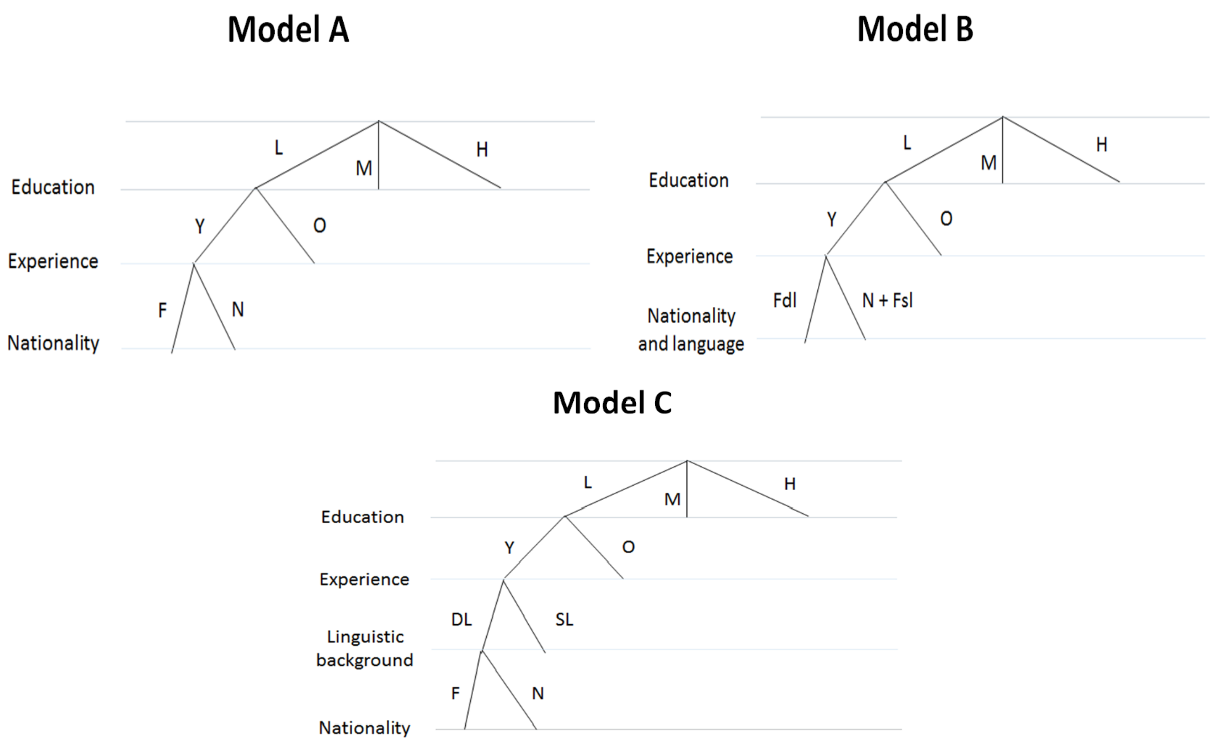
[26] It is also worth mentioning that these results should not be read as an exhaustive cost-benefit analysis of the free movement of persons, for at least two reasons. First, the welfare gains of Swiss workers that emigrated as a result of the bilateral agreements are not included in the analysis. Second, the bilateral agreements on the free movement of persons were enacted at the same time of other free trade agreements which may have had additional consequences on migration.

Figure 2.1: Linguistic areas across Switzerland



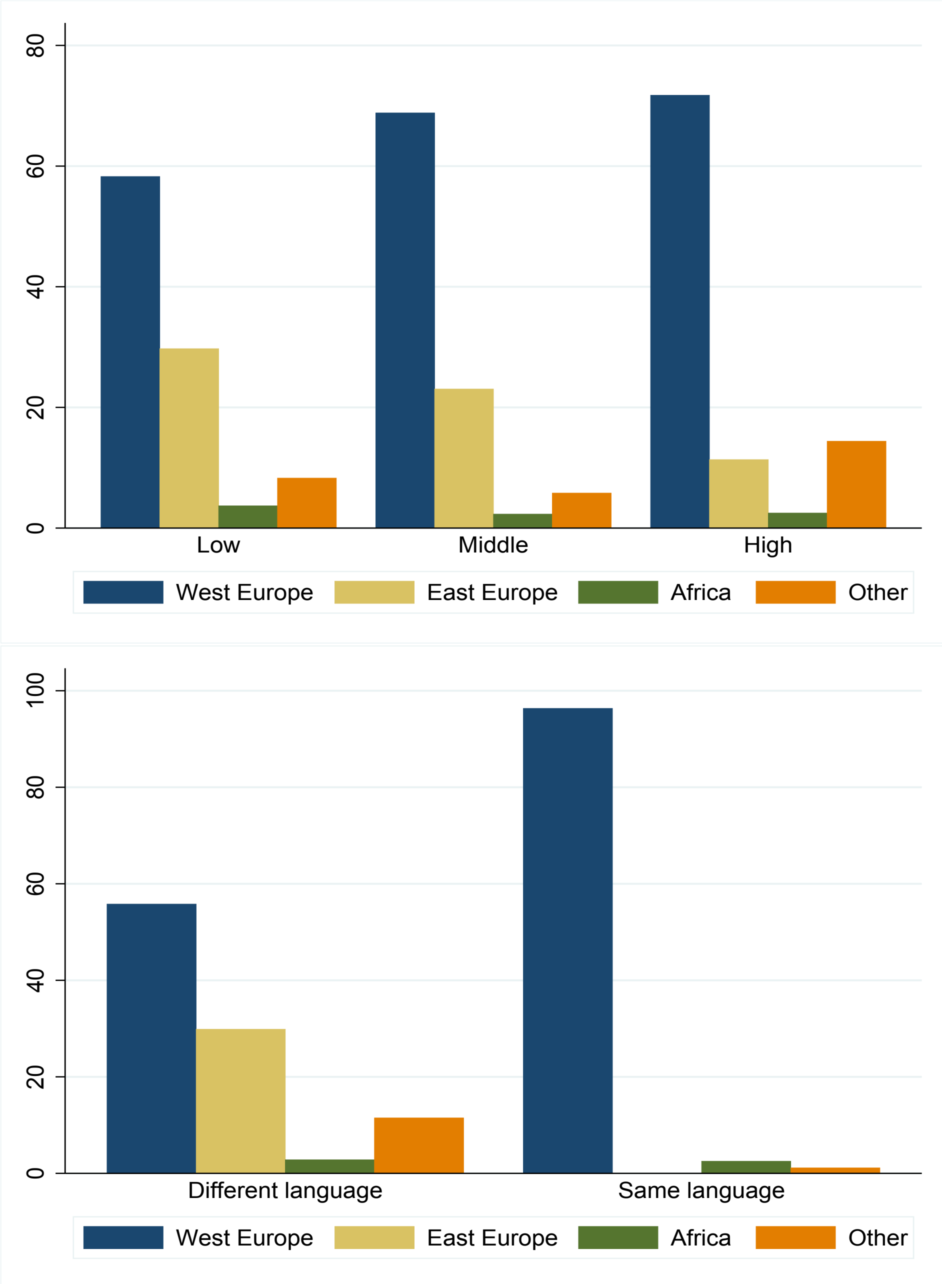
Notes - Colors correspond to different linguistic areas. Green corresponds to the French speaking area, brown to the German speaking area, purple to the Italian speaking area, and violet to the Romansh speaking area. Linguistic areas: FRE - French; GER - German; ROM - Romansh; ITA - Italian.
Sources: ©OFS, ThemaKart.

Figure 2.2: A comparison of the three models



Notes - Education groups are defined as: *Low education (L):* Compulsory education, elementary vocational training, household work, school for general education; *Middle education (M):* Apprenticeship, full-time vocational training, high school education, tertiary vocational training; *High education (H):* College education. Experience groups are defined as: *Young (Y):* up to 15 years of potential experience in the labor market; *Old (O):* Between 16 and 40 years of potential experience in the labor market. Linguistic background types are defined as: *Different linguistic background (DL)*; *Same linguistic background (SL)*. Nationality groups are defined as: *Foreigners (F)*; *Swiss Nationals (N)*. In model B the nationality groups are defined as: *Foreigners with different linguistic background (Fdl)*; *Swiss nationals (N); Foreigners with same linguistic background (Fsl).*

Figure 2.3: Share of foreign workers by area of origin, education and linguistic background group



Notes - Each bar represents the share of foreign workers by area of origin out of foreign workers within each education or linguistic background group. Individuals are classified as foreigners if they do not have Swiss citizenship. *West Europe* includes Andorra, Belgium, Denmark, Germany, Finland, France, Greece, UK, Ireland, Iceland, Italy, Liechtenstein, Luxemburg, Malta, Monaco, Netherlands, Norway, Austria, Portugal, San Marino, Sweden, Spain, Vatican City, Cyprus. *East Europe* includes Albania, Bulgaria, Poland, Romania, Turkey, Hungary, Slovakia, Czech Republic, Serbia, Croatia, Slovenia, Bosnia and Herzegovina, Montenegro, Macedonia, Kosovo, Estonia, Latvia, Lithuania, Moldova, Russia, Ukraine, Belarus. *Africa* includes African countries. *Other* includes foreign workers from North and South America, Asia and Oceania. Education groups are defined as: *Low education:* Compulsory education, elementary vocational training, household work, school for general education; *Middle education:* Apprenticeship, full-time vocational training, high school education, tertiary vocational training; *High education:* College education. Foreign workers are considered of different linguistic background if their country of citizenship has a different official language with respect to the language spoken in the linguistic area of residence in Switzerland. They are considered of same linguistic background otherwise.
Sources: SLFS - years 1999-2017.

Table 2.1: List of nationalities by linguistic background

Same linguistic background			Different linguistic background		
Nationality	Observations	Obs X Personal weights	Nationality	Observations	Obs X Personal weights
Germany	31,767	2,217,896	Italy	26,188	2,291,239
France	8,914	737,969	Portugal	16,675	1,869,561
Italy	7,548	400,037	Spain	7,467	744,334
Austria	3,879	308,181	Kosovo	6,609	597,693
Belgium	944	77,061	Turkey	4,512	518,293
Other	1,620	161,055	Other	53,573	5,038,211
Total	**54,672**	**3,902,199**	**Total**	**115,024**	**11,059,331**

Notes - Individuals are classified as foreigners if they do not have Swiss citizenship. Foreign workers are considered of different linguistic background if their country of citizenship has a different official language with respect to the language spoken in the linguistic area of residence in Switzerland. They are considered of same linguistic background otherwise.

Table 2.2: Percentage changes in natives' real wages and in hours worked by foreign workers

Education group	**Experience group**	**Linguistic group**	**% change in natives' real wages**	**% change in hours worked by foreign workers**
Low	Young	Different language	-48.6 %	-16.1 %
		Same language	-11.8 %	-36.5 %
	Old	Different language	-16.1 %	-14.2 %
		Same language	0.9 %	-23.5 %
Middle	Young	Different language	-16.1 %	-10.8 %
		Same language	-0.7 %	11.8 %
	Old	Different language	-1.2 %	50.6 %
		Same language	-0.4 %	16.9 %
High	Young	Different language	-8.9 %	287.9 %
		Same language	-9.4 %	154.5 %
	Old	Different language	-7.7 %	305.9 %
		Same language	-6.0 %	231.4 %

Notes - The percentage change in natives' real wages is the variation in natives' real wages between 1999 and 2017 out of natives' real wages in 1999. The percentage change in hours worked by foreign workers is the variation in hours worked by foreign workers between 1999 and 2017 out of hours worked by foreign workers in 1999. Individuals are classified as foreigners if they do not have Swiss citizenship. Education groups are defined as: *Low education:* Compulsory education, elementary vocational training, household work, school for general education; *Middle education:* Apprenticeship, full-time vocational training, high school education, tertiary vocational training; *High education:* College education. Foreign workers are considered of different linguistic background if their country of citizenship has a different official language with respect to the language spoken in the linguistic area of residence in Switzerland. They are considered of same linguistic background otherwise.

Table 2.3: Average intensity in communication skills by nationality, linguistic background and education

	Same linguistic background	Different linguistic background	t-test P-value
		Foreigners	
Low educated	60.1	53.4	0.000
Middle educated	64.9	60.2	0.000
High educated	73.1	71.1	0.000
		Natives	
Low educated	60.2	56.7	0.000
Middle educated	64.8	64.9	0.919
High educated	73.9	72.2	0.000

Notes - Importance scores for communication skills come from the O*NET database. Since occupations in the O*NET database are defined in terms of the Standard Occupational Classification (SOC), we convert them in the International Standard Classification of Occupations (ISCO-08) using the appropriate crosswalk. Then, we assign the scores to each individual in the SLFS according to the 4-digit ISCO-08 codes. Communication skills are the average importance scores of written and oral expression and written and oral comprehension. Average scores by education, nationality and linguistic background are aggregated weighting individual observations by hours worked times personal weight. Individuals are classified as foreigners if they do not have Swiss citizenship. Foreign workers are considered of different linguistic background if their country of citizenship has a different official language with respect to the language spoken in the linguistic area of residence in Switzerland. They are considered of same linguistic background otherwise. Education groups are defined as: *Low education:* Compulsory education, elementary vocational training, household work, school for general education; *Middle education:* Apprenticeship, full-time vocational training, high school education, tertiary vocational training; *High education:* College education. The p-values refer to mean comparison tests without controls. The mean comparison tests are also robust to the inclusion of education, experience, gender and a dummy variable for European foreigners. In performing the mean comparison tests, the observations are weighted by hours worked times personal weights.

Table 2.4: Occupations of middle educated workers by nationality

Occupation category	**Foreign workers**	**Native workers**	**Total**
Managers	5,238	16,679	21,917
	(7.18 %)	(7.97 %)	(7.77 %)
Professionals	9,535	37,309	46,844
	(13.08 %)	(17.84 %)	(16.61 %)
Technicians and Associate Professionals	14,895	50,152	65,047
	(20.43 %)	(23.98 %)	(23.06 %)
Clerical Support Workers	6,860	29,870	36,730
	(9.41 %)	(14.28 %)	(13.02 %)
Service and Sales Workers	13,889	31,548	45,437
	(19.05 %)	(15.08 %)	(16.11 %)
Skilled Agricultural, Forestry and Fishery Workers	559	6,587	7,146
	(0.77 %)	(3.15 %)	(2.53 %)
Craft and Related Trades Workers	14,002	26,139	40,141
	(19.21 %)	(12.50 %)	(14.23 %)
Plant and Machine Operators and Assemblers	4,395	6,746	11,141
	(6.03 %)	(3.23 %)	(3.95 %)
Elementary Occupations	3,534	4,134	7,668
	(4.85 %)	(1.98 %)	(2.72 %)
Total	72,907	209,164	282,071
	(100.00 %)	(100.00 %)	(100.00 %)

Notes - Individuals are classified as foreigners if they do not have Swiss citizenship. Middle educated workers are defined as workers with apprenticeship, full-time vocational training, high school education, or tertiary vocational training. Occupation categories are defined according to the International Standard Classification of Occupations (ISCO-08): managers correspond to the ISCO category 1, professionals correspond to the ISCO category 2, etc.

Table 2.5: Estimated coefficients for nationality groups

	Model A			Model B			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of hours worked	-0.038	-0.081***	-0.048**	-0.124***	-0.128***	-0.112***	-0.011	-0.010	0.010
	(0.03)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Observations	114	114	114	114	114	114	227	227	227
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	No	No	No	Yes

Notes - Fixed effect estimates. Model A: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model B: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers with different linguistic background and the number of native workers and foreign workers with the same linguistic background by cell. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.6: Job specialization according to communication skills - Models A and C

	Model A			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)
Log hours worked	-0.022**	-0.026**	-0.059**	-0.015	-0.011	-0.019***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)
Observations	114	114	114	228	228	228
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	Yes

Notes - Fixed effect estimates. All the estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model A: Group fixed effects are the interaction of education and experience fixed effects. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The dependent variable is the logarithm of the ratio between the average intensity of communication skills of foreigners and the average intensity of communication skills of natives by cell. Communication skills consist of the average importance scores of written and oral expression and written and oral comprehension. Importance scores for communication skills come from the O*NET database. Since occupations in the O*NET database are defined in terms of the Standard Occupational Classification (SOC), we convert them in the International Standard Classification of Occupations (ISCO-08) using the appropriate crosswalk. Then, we assign the scores to each individual in the SLFS according to the 4-digit ISCO-08 codes. The average intensity of communication skills by cell is obtained weighting individual observations by the number of hours worked times the personal weight and averaging them by cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.7: Simulated long run and short run effects on real wages (in percentage points)

PANEL A

Percentage wage impact on native workers

Column	(1) Long run 1999–2017	(2) Short run 1999–2001	(3) Short run 2002–2008	(4) Short run 2009–2017
Low educated	4.8	0.1	-1.6	1.0
	(0.6)	(0.2)	(0.0)	(0.4)
Middle educatd	2.7	-0.3	-0.3	-0.6
	(0.3)	(0.0)	(0.2)	(0.1)
High educated	-11.5	-0.3	-6.4	-3.4
	(1.6)	(0.0)	(0.7)	(0.3)
Average natives	**0.7**	**-0.3**	**-1.4**	**-1.4**
	(0.5)	**(0.0)**	**(0.2)**	**(0.2)**

PANEL B

Percentage wage impact on foreign workers

Column	(1) Long run 1999–2017	(2) Short run 1999–2001	(3) Short run 2002–2008	(4) Short run 2009–2017
Low educated	5.8	0.1	-2.4	1.7
	(0.6)	(0.2)	(0.1)	(0.4)
Middle educated	1.8	-0.8	0.1	-1.3
	(0.3)	(0.1)	(0.2)	(0.1)
High educated	-22.3	-1.1	-11.4	-5.4
	(1.6)	(0.0)	(0.7)	(0.3)
Average foreigners	**-3.0**	**-0.7**	**-3.3**	**-2.6**
	(0.7)	**(0.1)**	**(0.3)**	**(0.2)**
Overall average	**0.0**	**-0.3**	**-1.8**	**-1.7**
	(0.5)	**(0.0)**	**(0.2)**	**(0.2)**

Notes - The simulated effects and standard errors are in percentage points. Years 1999–2001 correspond to the period prior to the enactment of the free movement of persons. Years 2002-2008 correspond to the period between the enactment of the free movement of persons and the start of the economic crisis. Years 2009-2017 correspond to the aftermath of the economic crisis. To compute the simulated wage effects and their standard errors we start from our preferred estimates of the elasticities of substitution. As discussed in Appendix 2.A, the relevant parameters are the inverse of the elasticities of substitution (i.e. the estimated coefficients). For each parameter, we perform 5,000 random draws from a joint normal distribution and we compute the percentage wage changes according to Equations (2.9) and (2.10) in Appendix 2.A. Particularly, we plug in the normal distribution a beta coefficient of 0.010 for nationality groups, 0.085 for linguistic background groups, 0.185 for experience groups and 0.257 for education groups. Then, we average the simulated percentage wage changes and we compute their standard deviations. Finally, we aggregate up these average percentage wage changes weighting each education-experience-linguistic background wage change by the relative wage share of the group. We compute standard errors by education and by nationality using the same weighting procedure. In simulating long run effects, we consider a variation in the capital-labor ratio equal to 0, while in simulating short run effects we consider capital as fixed, i.e. a variation in the capital-labor ratio equal to minus the variation in the labor force due to immigration.

Appendix

2.A Theoretical appendix

Total wage impact of immigration

To compute the percentage wage change by cell, we perform 5,000 random draws from a jointly normal distribution using the estimated elasticities of substitution as key parameters. Following OP, we define the mean of the normal distribution as the estimated parameter, and the standard deviation as the estimated standard error multiplied by the square root of 12, i.e. the number of observations. In this way we obtain 5,000 random realizations for each elasticity of substitution and we average them across observations. Then, from Equation (2.3), at each draw we compute the simulated percentage wage change for foreigners and natives as:

$$\begin{aligned}\frac{\Delta\omega_{Fkjlt}}{\omega_{Fkjlt}} =& \frac{1}{\sigma_{edu}}\sum_{e=1}^{3}\sum_{q=1}^{2}\sum_{i=1}^{2}\left(s_{Feqit}\frac{\Delta F_{eqit}}{F_{eqit}}\right) + \left(\frac{1}{\sigma_{exp}} - \frac{1}{\sigma_{edu}}\right)\left(\frac{1}{s_{kt}}\right)\sum_{q=1}^{2}\sum_{i=1}^{2}\left(s_{Fkqit}\frac{\Delta F_{kqit}}{F_{kqit}}\right) + \\ & + \left(\frac{1}{\sigma_{lan}} - \frac{1}{\sigma_{exp}}\right)\left(\frac{1}{s_{kjt}}\right)\sum_{i=1}^{2}\left(s_{kjit}\frac{\Delta F_{kjit}}{F_{kjit}}\right) + \left(\frac{1}{\sigma_{nat}} - \frac{1}{\sigma_{lan}}\right)\left(\frac{1}{s_{kjlt}}\frac{\Delta F_{kjlt}}{F_{kjlt}}\right) + \\ & + (1-\alpha)\frac{\Delta\kappa_t}{\kappa_t} - \frac{1}{\sigma_{nat}}\frac{\Delta F_{kjlt}}{F_{kjlt}}\end{aligned} \tag{2.9}$$

and:

$$\begin{aligned}\frac{\Delta\omega_{Nkjlt}}{\omega_{Nkjlt}} =& \frac{1}{\sigma_{edu}}\sum_{e=1}^{3}\sum_{q=1}^{2}\sum_{i=1}^{2}\left(s_{Feqit}\frac{\Delta F_{eqit}}{F_{eqit}}\right) + \left(\frac{1}{\sigma_{exp}} - \frac{1}{\sigma_{edu}}\right)\left(\frac{1}{s_{kt}}\right)\sum_{q=1}^{2}\sum_{i=1}^{2}\left(s_{Fkqit}\frac{\Delta F_{kqit}}{F_{kqit}}\right) + \\ & + \left(\frac{1}{\sigma_{lan}} - \frac{1}{\sigma_{exp}}\right)\left(\frac{1}{s_{kjt}}\right)\sum_{i=1}^{2}\left(s_{kjit}\frac{\Delta F_{kjit}}{F_{kjit}}\right) + \left(\frac{1}{\sigma_{nat}} - \frac{1}{\sigma_{lan}}\right)\left(\frac{1}{s_{kjlt}}\frac{\Delta F_{kjlt}}{F_{kjlt}}\right) + \\ & + (1-\alpha)\frac{\Delta\kappa_t}{\kappa_t}\end{aligned} \tag{2.10}$$

where $\Delta\omega_{Fkjlt}/\omega_{Fkjlt}$ represents the percentage variation in the wage of foreign workers F in education group k, experience group j, linguistic background group l, at time t. To the same extent,

$\Delta\omega_{Nkjlt}/\omega_{Nkjlt}$ represents the percentage variation in the wage of native workers. The summation subscripts e, q, and i refer respectively to education, experience and linguistic background groups. $\Delta F_{kjlt}/F_{kjlt}$ represents the percentage variation in the number of hours worked by foreign workers, while $\Delta\kappa_t/\kappa_t$ is the percentage variation in the capital-labor ratio, as discussed below. Finally, the s-variables refer to the wage shares. For instance, the wage share of foreign workers in education group k, experience group j and linguistic background group l at time t can be written as:

$$s_{Fkjlt} = \frac{\omega_{Fkjlt}F_{kjlt}}{\sum_{e=1}^{3}\sum_{q=1}^{2}\sum_{i=1}^{2}(\omega_{Feqit}F_{eqit} + \omega_{Neqit}N_{eqit})} \tag{2.11}$$

To the same extent, the overall wage share for education group k, experience group j and linguistic background group l is:

$$s_{kjlt} = \frac{\omega_{Fkjlt}F_{kjlt} + \omega_{Nkjlt}N_{kjlt}}{\sum_{e=1}^{3}\sum_{q=1}^{2}\sum_{i=1}^{2}(\omega_{Feqit}F_{eqit} + \omega_{Neqit}N_{eqit})} \tag{2.12}$$

Thus, we end up with 5,000 simulated percentage wage changes for native and foreign workers. We compute the mean and the standard deviation of such wage changes by education, experience, and linguistic background. Finally, we compute average percentage wage changes by education group and their standard deviations weighting each wage change by its relative wage share. For instance, percentage variations in native average wages by education group can be written as:

$$\frac{\Delta\bar{\omega}_{Nkt}}{\bar{\omega}_{Nkt}} = \sum_{q=1}^{2}\sum_{i=1}^{2}\left(\frac{\Delta\omega_{Nkqit}}{\omega_{Nkqit}}s_{Nkqit}\right) \tag{2.13}$$

Standard errors by education group are computed averaging the standard errors in the same way. Following the same reasoning, it is possible to obtain average percentage wage changes for native and foreign workers, as well as the overall wage impact on the economy.

Long run and short run simulations

As discussed in the main text, while in the long run immigration flows have zero impact on wages, in the short run immigration affects individual wages through an additional term, i.e. the capital-labor ratio κ (see the optimality condition in Equation (2.3)). Particularly, the magnitude of this effect can be derived from the Cobb-Douglas production function. Consider the marginal productivity of labor:

$$\omega_t = \frac{\partial Y_t}{\partial L_t} = \alpha A\kappa_t^{(1-\alpha)} \tag{2.14}$$

where κ is the capital-labor ratio K/L. Assuming that total factor productivity A_t does not depend on immigration flows, the percentage variation in average wages can be written as:

$$\frac{\Delta\omega_t}{\omega_t} = (1-\alpha)\frac{\Delta\kappa_t}{\kappa_t} \tag{2.15}$$

With fixed capital, the variation in κ only depends on the denominator, i.e. the increase in the labor force due to migration. Thus, this equation can be rewritten as:

$$\frac{\Delta\omega_t}{\omega_t} = (1-\alpha)\left(-\frac{\Delta F_t}{L_t}\right) \tag{2.16}$$

where ΔF_t represents the inflow of foreign workers in the period considered.

Accordingly, in our short run simulation we decrease the average wage effect computed in each random draw by a constant equal to $(1-\alpha)(\Delta F_t/L_t)$. The second term is just the percentage change in the labor force due to foreign workers in the period considered, while the first term is the share of income going to capital. Since in Switzerland the labor income share between 1970 and 2012 has been approximately 62% (OECD, 2016b), we assume $(1-\alpha) = 38$.

2.B Further data details

This appendix contains the description of the data used. Particularly, Sections 2.B.1-2.B.4 contain a detailed description of the criteria used to group workers into education, experience, nationality and linguistic background groups. Then, Sections 2.B.5 and 2.B.6 describe how the labor and wage aggregates are defined. Section 2.B.7 contains information about the Swiss Earnings Structure Survey data, and how the shares of cross-border workers are imputed to SLFS cells. Finally, Section 2.B.8 describes the construction of the measures of communication skills.

2.B.1 Education groups

- Low education: Compulsory education (TBQ1=1), elementary vocational training (TBQ1=2), household work (TBQ1=3), school for general education (TBQ1=4);
- Middle education: Apprenticeship (TBQ1=5), full-time vocational training (TBQ1=6), high school education (TBQ1=7), tertiary vocational training (TBQ1=8);
- High education: College (TBQ1=9)

2.B.2 Experience groups

We assign people to experience groups according to years of potential experience. Potential experience is computed as the difference between current age and the age at which an individual should have completed the maximum level of education achieved. For this reason, we assume that people enter the labor market at the age 14 if they only obtained compulsory education, at age 16 if they accomplished elementary vocational training, household work or school for general education, at age 18 if they accomplished apprenticeship or full-time vocational education, at age 19 if they obtained a high school degree, at age 22 if they accomplished tertiary vocational education and at age 24 if they accomplished college education. Also, we drop from the sample individuals with experience smaller than zero and greater than 40.

2.B.3 Nationality groups

National groups are defined according to citizenship. There are three ways to obtain Swiss citizenship: birth, marriage and naturalization. Citizenship by birth is acknowledged to children of Swiss parents. People married to a Swiss person can apply for fast naturalization track after three years of marriage and at least 5 years of residence in Switzerland. Finally, every immigrant can apply for naturalization after at least 12 years of permanence in Switzerland. Moreover, there is a three-tiered process, in which the State Secretariat for Migration, the Cantons (i.e. the states of the Swiss confederation) and the municipalities are all involved in the naturalization procedure. To acquire the citizenship an immigrant must first apply to the State Secretariat for Migration, which evaluates the applicant situation, her knowledge of Swiss customs and how much she is integrated into the Swiss society. Then, if the Secretariat decides that the applicant can receive the citizenship, the Canton and the municipality of residence must also evaluate the application with their own requirements. Sometimes municipalities require the applicant to undertake a written or an oral exam. At every step of the process the naturalization of the applicant can be rejected.

2.B.4 Linguistic background groups

Linguistic background groups are defined according to the area of residence. Swiss nationals are classified as "same linguistic background" if they complete the questionnaire in the same language as the linguistic area of residence, while they are classified as "different linguistic background" otherwise. To the same extent, immigrants are considered as "same linguistic background" when the official language of their country of citizenship coincides with the language spoken in the linguistic area of residence in Switzerland, and they are classified as "different linguistic background" otherwise. Here is the list of citizenships which are considered of German, French or Italian background.

- Countries with German speaking background: Germany, Austria.
- Countries with French speaking background: France, Belgium, Luxembourg, Canada, Monaco, Democratic Republic of the Congo, Republic of the Congo, Saint Martin (French part), Madagascar, Cameroon, Senegal, Rwanda, Haiti, Chad, Guinea, Benin, Central African Republic, Gabon, Comoros, Equatorial Guinea, Djibouti, Seychelles, New Caledonia, French Polyne-

sia, Guernsey, Wallis and Futuna, French Southern and Antarctic Lands, Sark, Mauritius, Réunion, Guadeloupe, French Guyana, Martinique, Saint Pierre and Miquelon, Saint Lucia, Saint Barthélemy, French Indochina, French Polynesia, Burkina Faso, Niger, Mali, Burundi, Togo, Vanuatu, Cote d'Ivoire.

- Countries with Italian speaking background: Italy, San Marino, Vatican City.

2.B.5 labor aggregate

To compute the labor aggregate we:

- Drop people below 18 years old (BB03A<18);
- Drop people in military service, unemployed, in education or inactive (BDU1>9);
- Keep people with remunerated labor in the previous week (BD01=1).

To compute the total weekly hours supplied, we focus on hours actually worked and we sum hours provided within the main job (EK08) with hours provided within the secondary job (EK08N). Then, we drop the observations for which this sum was zero or missing. Finally, we aggregate the hours worked multiplying the hours worked by personal weights and then summing up by cell.

2.B.6 Wages

To compute the average wages we:

- Drop people below 18 years old (BB03A<18);
- Drop people in military service, unemployed, in education or inactive (BDU1>9);
- Keep people with remunerated labor in the previous week (BD01=1).

Since in the SLFS there are only yearly data without indication of how many weeks per year the individual worked, we divide net annual income (BWU2) by 52. Then, we drop the observations for which income was zero and we trim the upper and lower 1% of the income distribution. Finally, we compute real wages deflating the nominal wages by the consumer price index.

2.B.7 Cross-border workers

The Swiss Earnings Structure Survey (SESS) is a biannual survey administered to approximately 35,000 firms about the earnings of employees in the secondary and tertiary sectors, including cross-border workers. However, since the SESS has no information about the foreign workers country of origin, we assume that all cross-border workers share the same linguistic background of the linguistic area where they work. From the SESS we compute the incidence of cross-border workers out of foreign population by cell, both for labor and wage aggregates. Then, we inflate our wage and labor aggregates according to these shares. Finally, since the SESS is biannual, we linearly interpolate the missing years.

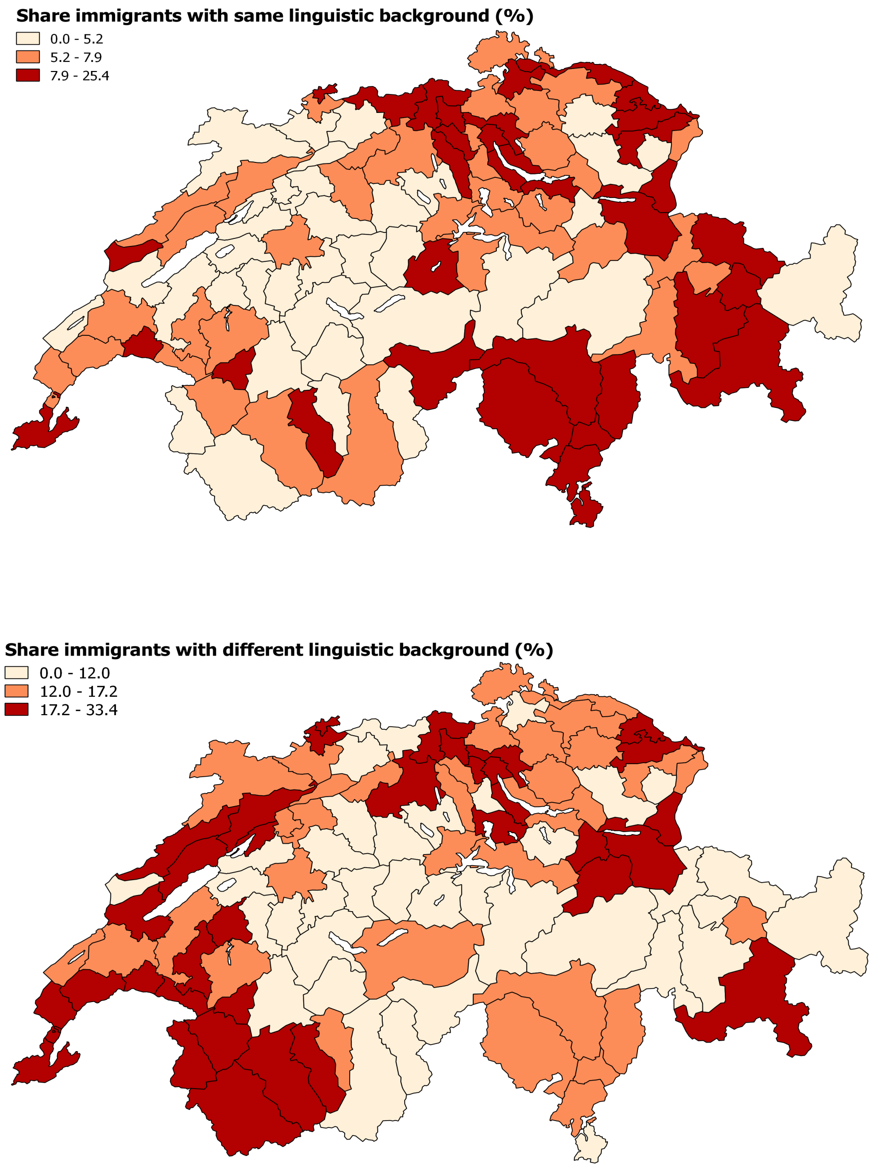
2.B.8 Measures of communication skills

To measure the importance of communication skills we rely on the information contained in the O*NET database. In particular, for each communication skill of interest we download the list of its importance scores by occupation. Since occupations in the O*NET database are defined in terms of the Standard Occupational Classification (SOC), we convert them in the International Standard Classification of Occupations (ISCO-08) using the appropriate crosswalk. Then, we assign the scores to each individual in the SLFS according to the 4-digit ISCO-08 codes. Finally, we compute the average communication skills by cell weighting each individual by the number of hours worked times his/her personal weight. In the following, we list the skills that we include in our baseline and extended definitions of communication skills.

- **Communication skills:**
  - *Oral:* Oral comprehension; Oral expression.
  - *Written:* Written comprehension; Written expression.
- **Extended communication skills:**
  - *Oral:* Oral comprehension; Oral expression.
  - *Written:* Written comprehension; Written expression.
  - *Cognitive and analytical skills:* Category flexibility; Deductive reasoning; Flexibility of closure; Fluency of ideas; Inductive reasoning; Information ordering; Mathematical reasoning; Memorization; Number facility; Originality; Problem sensitivity; Speed of closure.
  - *Vocal skills:* Speech clarity; Speech recognition.

2.C Additional figures and tables

Figure 2.C.1: Incidence of immigrants with same and different linguistic background out of total population by spatial mobility region



Notes - Share of immigrants with same and different linguistic background out of total population by spatial mobility region. Individuals are classified as foreigners if they do not have Swiss citizenship. Foreign workers are considered of different linguistic background if their country of citizenship has a different official language with respect to the language spoken in the linguistic area of residence in Switzerland. They are considered of same linguistic background otherwise. The number of immigrants and resident popualtion by spatial mobility region are obtained summing up individual weights. Intervals depicted in different colors correspond to terciles.

Sources: Base maps: ©OFS, ThemaKart; Data: SLFS - year 2013.

Table 2.C.1: Average intensity in communication skills by nationality, linguistic background and education - extended definition

	Same linguistic background	Different linguistic background	t-test P-value
		Foreigners	
Low educated	51.3	46.8	0.000
Middle educated	55.2	51.7	0.000
High educated	62.3	60.6	0.000
		Natives	
Low educated	50.9	49.1	0.000
Middle educated	54.9	54.8	0.677
High educated	62.4	60.9	0.000

Notes - Importance scores for communication skills come from the O*NET database. Since occupations in the O*NET database are defined in terms of the Standard Occupational Classification (SOC), we convert them in the International Standard Classification of Occupations (ISCO-08) using the appropriate crosswalk. Then, we assign the scores to each individual in the SLFS according to the 4-digit ISCO-08 codes. The extended definition of communication skills is described in Appendix 2.B.8. Average scores by education, nationality and linguistic background are aggregated weighting individual observations by hours worked times personal weight. Individuals are classified as foreigners if they do not have Swiss citizenship. Foreign workers are considered of different linguistic background if their country of citizenship has a different official language with respect to the language spoken in the linguistic area of residence in Switzerland. They are considered of same linguistic background otherwise. Education groups are defined as: *Low education:* Compulsory education, elementary vocational training, household work, school for general education; *Middle education:* Apprenticeship, full-time vocational training, high school education, tertiary vocational training; *High education:* College education. The p-values refer to mean comparison tests without controls. The mean comparison tests are also robust to the inclusion of education, experience, gender and a dummy variable for European foreigners. In performing the mean comparison tests, the observations are weighted by hours worked times personal weights

Table 2.C.2: Occupations of highly educated workers by nationality

Occupation category	**Foreign workers**	**Native workers**	**Total**
Managers	8,349	8,079	16,428
	(18.95 %)	(13.83 %)	(16.03 %)
Professionals	24,631	38,930	63,561
	(55.90 %)	(66.65 %)	(62.03 %)
Technicians and Associate Professionals	6,183	7,231	13,414
	(14.03 %)	(12.38 %)	(13.09 %)
Clerical Support Workers	1,346	1,530	2,876
	(3.05 %)	(2.62 %)	(2.81 %)
Service and Sales Workers	2,012	1,588	3,600
	(4.57 %)	(2.72 %)	(3.51 %)
Skilled Agricultural, Forestry and Fishery Workers	84	178	262
	(0.19 %)	(0.30 %)	(0.26 %)
Craft and Related Trades Workers	715	568	1,283
	(1.62 %)	(0.97 %)	(1.25 %)
Plant and Machine Operators and Assemblers	374	178	552
	(0.85 %)	(0.30 %)	(0.54 %)
Elementary Occupations	367	128	495
	(0.83 %)	(0.22 %)	(0.48 %)
Total	44,061	58,410	102,471
	(100.00 %)	(100.00 %)	(100.00 %)

Notes - Individuals are classified as foreigners if they do not have Swiss citizenship. Highly educated workers are defined as workers with college degree. Occupation categories are defined according to the International Standard Classification of Occupations (ISCO-08): managers correspond to the ISCO category 1, professionals correspond to the ISCO category 2, etc.

Table 2.C.3: Estimated coefficients for linguistic background groups

	Model C		
Column	(1)	(2)	(3)
Log of hours worked	-0.068***	-0.324*	-0.085***
	(0.01)	(0.19)	(0.01)
Observations	227	227	227
Kleibergen-Paap F	145	3	433
Group fixed effects	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes
Time by education FE	No	Yes	Yes
Linguistic, exp. and educ. FE	No	No	Yes
Linguistic by education FE	No	No	Yes

Notes - IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. All the estimates are weighted by the number of workers in each education-experience-linguistic background cell. Group fixed effects are the interaction of education, experience and linguistic background fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Table 2.C.4: Estimated coefficients for experience groups

	Model A		Model B		Model C	
Column	(1)	(2)	(3)	(4)	(5)	(6)
Log of hours worked	-0.053***	-0.105*	-0.052***	-0.110***	-0.054***	-0.185**
	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.07)
Observations	114	114	114	114	114	114
Kleibergen-Paap F	553	10	549	34	540	10
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	No	Yes	No	Yes

Notes - Models A and C: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. Model B: IV estimates using the logarithm of the number of hours provided by foreign workers with different linguistic background as an instrument for the logarithm of the number of hours provided. All the estimates are weighted by the number of workers in each education-experience cell. Group fixed effects are the interaction of education and experience fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Table 2.C.5: Estimated coefficients for education groups

	Model A	Model B	Model C
Column	(1)	(2)	(3)
Log of hours worked	-0.153***	-0.117*	-0.257***
	(0.06)	(0.06)	(0.09)
Observations	57	57	57
Kleibergen-Paap F	15	9	14
Education fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Education trends	Yes	Yes	Yes

Notes - Models A and C: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. Model B: IV estimates using the logarithm of the number of hours provided by foreign workers with different linguistic background as an instrument for the logarithm of the number of hours provided. All the estimates are weighted by the number of workers in each education cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Table 2.C.6: Estimated coefficients for linguistic background groups holding nationality fixed

Column	(1)	(2)	(3)
Log of hours worked	-0.114*	-0.146***	-0.089**
	(0.06)	(0.04)	(0.03)
Observations	227	227	227
Group fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Time by education FE	No	Yes	Yes
Time by experience FE	No	No	Yes
Time by nationality FE	No	No	Yes

Notes - Fixed effect estimates. This model has been obtained inverting the linguistic background and the nationality characteristics in model C. All the estimates are weighted by the ratio between the number of workers with different linguistic background and the number of workers with same linguistic background by cell. Group fixed effects are the interaction of education, experience and nationality fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.C.7: Job specialization according to communication skills (extended definition) - Models A and C

	Model A			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)
Log hours worked	-0.018**	-0.022**	-0.045*	-0.010	-0.006	-0.010**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)
Observations	114	114	114	228	228	228
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	Yes

Notes - Fixed effect estimates. All the estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model A: Group fixed effects are the interaction of education and experience fixed effects. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The dependent variable is the logarithm of the ratio between the average intensitity of communication skills of foreigners and the average intensity of communication skills of natives by cell. The extended definition of communication skills includes cognitive, analytical and vocal skills in addtion to written and oral expression and written and oral comprehension. Further details on the extended definition of communication skills can be found in Appendix 2.B.8. Scores for communication skills come from the O*NET database. Since occupations in the O*NET database are defined in terms of the Standard Occupational Classification (SOC), we convert them in the International Standard Classification of Occupations (ISCO-08) using the appropriate crosswalk. Then, we assign the scores to each individual in the SLFS according to the 4-digit ISCO-08 codes. The average intensity of communication skills by cell is obtained weighting individual observations by the number of hours worked times the personal weight and averaging them by cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.C.8: Estimated coefficients for nationality groups by gender

	Model A			Model B			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Men	-0.045	-0.03	-0.090***	-0.059	-0.027***	-0.019	-0.109	-0.020	0.179**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)	(0.03)	(0.06)	(0.03)	(0.06)
Observations	114	114	114	114	114	114	220	220	220
Women	-0.032	-0.083	-0.024	-0.128	-0.138	0.000	0.112**	0.136***	0.097
	(0.08)	(0.07)	(0.04)	(0.07)	(0.08)	(0.02)	(0.04)	(0.03)	(0.09)
Observations	114	114	114	114	114	114	219	219	219
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	No	No	No	Yes

Notes - Fixed effect estimates. Model A: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model B: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers with different linguistic background and the number of native workers and foreign workers with the same linguistic background by cell. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Given the small number of observations by cell and the large number of cells, in model C we discard the cells in the first and last percentile of the labor supply distribution. This trimming created 6 missing cells. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.C.9: Estimated coefficients for linguistic background groups by gender

	Model C		
Column	(1)	(2)	(3)
Men	-0.068***	-0.450	-0.056***
	(0.02)	(0.40)	(0.02)
Observations	225	225	225
Kleibergen-Paap F	42	2	122
Women	0.008	0.161**	-0.032**
	(0.01)	(0.08)	(0.02)
Observations	224	224	224
Kleibergen-Paap F	247	17	692
Group fixed effects	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes
Time by education FE	No	Yes	Yes
Linguistic, exp. and educ. FE	No	No	Yes
Linguistic by education FE	No	No	Yes

Notes - IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. All the estimates are weighted by the number of workers in each education-experience-linguistic background cell. Group fixed effects are the interaction of education, experience and linguistic background fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Table 2.C.10: Estimated coefficients for experience groups by gender

	Model A		Model B		Model C	
Column	(1)	(2)	(3)	(4)	(5)	(6)
Men	-0.046***	-0.167**	-0.051***	-0.213***	-0.066**	-0.731*
	(0.01)	(0.08)	(0.01)	(0.08)	(0.03)	(0.39)
Observations	114	114	114	114	114	114
Kleibergen-Paap F	370	9	449	16	250	4
Women	0.014	0.263***	0.016	0.215***	0.041**	0.356***
	(0.01)	(0.06)	(0.01)	(0.05)	(0.02)	(0.07)
Observations	114	114	114	114	114	114
Kleibergen-Paap F	660	40	402	81	555	38
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	No	Yes	No	Yes

Notes - Models A and C: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. Model B: IV estimates using the logarithm of the number of hours provided by foreign workers with different linguistic background as an instrument for the logarithm of the number of hours provided. All the estimates are weighted by the number of workers in each education-experience cell. Group fixed effects are the interaction of education and experience fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Table 2.C.11: Estimated coefficients for education groups by gender

	Model A	Model B	Model C
Column	(1)	(2)	(3)
Men	-0.136***	-0.119**	-0.434**
	(0.05)	(0.05)	(0.21)
Observations	57	57	57
Kleibergen-Paap F	14	11	9
Women	0.080*	0.081*	0.004
	(0.04)	(0.05)	(0.13)
Observations	57	57	57
Kleibergen-Paap F	21	15	18
Education fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Education trends	Yes	Yes	Yes

Notes - Models A and C: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. Model B: IV estimates using the logarithm of the number of hours provided by foreign workers with different linguistic background as an instrument for the logarithm of the number of hours provided. All the estimates are weighted by the number of workers in each education cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity.

Table 2.C.12: Estimated coefficients for nationality groups - cross-border workers included

	Model A			Model B			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of hours worked	-0.033	-0.078***	-0.051	-0.118***	-0.117***	-0.099***	-0.011	-0.010	0.010
	(0.04)	(0.01)	(0.03)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)
Observations	114	114	114	114	114	114	227	227	227
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	No	No	No	Yes

Notes - Fixed effect estimates. Data on cross-border workers comes from the Swiss Earnings Structure Survey (SESS). Particularly, with SESS data we compute the incidence of cross-border workers out of foreign population by cell, both for labor and wage aggregates. Then, we inflate our wage and labor aggregates according to these shares. Since SESS data are biannual, we linearly interpolate the incidence of cross-border workers in missing years. Moreover, since the SESS does not contain any information about the nationality of workers, we assume that all the cross-border workers share the language of the linguistic area where they work. Model A: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model B: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers with different linguistic background and the number of native workers and foreign workers with the same linguistic background by cell. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.C.13: Model C - linguistic background and experience characteristics inverted

Column	β_{nat} (1)	β_{nat} (2)	β_{nat} (3)	β_{exp} (4)	β_{exp} (5)	β_{lan} (6)	β_{lan} (7)	β_{edu} (8)
Log of hours worked	-0.011	-0.010	0.010	-0.068***	-0.085***	-0.064***	0.047***	-0.314***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.11)
Observations	227	227	227	227	227	114	114	57
Kleibergen-Paap F				145	433	90	120	18
Group fixed effects	Yes	Yes	Yes	Yes	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	No	Yes	No
Time by linguistic back. FE	No	No	Yes	No	No	No	No	No
Time by experience FE	No	No	Yes	No	No	No	No	No
Education FE	No	No	No	No	Yes	No	Yes	No
Linguistic back. FE	No	No	No	No	Yes	No	Yes	No
Experience FE	No	No	No	No	Yes	No	No	No
Linguistic b. by education FE	No	No	No	No	Yes	No	No	No
Education trends	No	No	No	No	No	No	No	Yes

Notes - β_{nat}: Fixed effects estimates. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Group fixed effects are the interaction of education, linguistic background and experience fixed effects. β_{exp}: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. The estimates are weighted by the number of workers in each education-linguistic background-experience cell. Group fixed effects are the interaction of education, linguistic background and experience fixed effects. β_{lan}: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. The estimates are weighted by the number of workers in each education-linguistic background cell. Group fixed effects are the interaction of education and linguistic background fixed effects. β_{edu}: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. The estimates are weighted by the number of workers in each education cell. Group fixed effects are just education fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity. Standard errors for β_{nat} are clustered at group level.

Table 2.C.14: Model A - Estimated coefficients for education, experience and nationality groups - different experience groups

Column	β_{nat} (1)	β_{nat} (2)	β_{exp} (3)	β_{exp} (4)	β_{edu} (5)
			8 experience groups		
Log of hours worked	0.007	0.010	-0.034***	-0.032	-0.186**
	(0.04)	(0.04)	(0.01)	(0.02)	(0.07)
Observations	456	456	456	456	57
Kleibergen-Paap F			541	137	14
			3 experience groups		
Log of hours worked	-0.020	-0.029	-0.048***	-0.042***	-0.154***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.06)
Observations	171	171	171	171	57
Kleibergen-Paap F			530	59	15
Group fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	No	Yes	No
Education trends	No	No	No	No	Yes

Notes - β_{nat}: Fixed effects estimates. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Group fixed effects are the interaction of education and experience fixed effects. β_{exp}: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. The estimates are weighted by the number of workers in each education-experience cell. Group fixed effects are the interaction of education and experience fixed effects. β_{edu}: IV estimates using the logarithm of the number of hours provided by foreign workers as an instrument for the logarithm of the number of hours provided. The estimates are weighted by the number of workers in each education cell. Group fixed effects are just education fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity. Standard errors for β_{nat} are clustered at group level.

Table 2.C.15: Estimated coefficients for nationality groups - different education groups

	Model A			Model B			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Middle and High educated grouped together					
Log of hours worked	-0.031	-0.081***	-0.054***	-0.115**	-0.133***	-0.089***	-0.045	-0.055**	0.019*
	(0.04)	(0.01)	(0.00)	(0.03)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Observations	76	76	76	76	76	76	151	151	151
				Low and Middle educated grouped together					
Log of hours worked	-0.045	-0.055**	0.019*	-0.102	-0.061***	-0.074***	0.057	0.064	-0.111***
	(0.05)	(0.01)	(0.01)	(0.07)	(0.01)	(0.01)	(0.06)	(0.07)	(0.01)
Observations	76	76	76	76	76	76	152	152	152
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	No	No	No	Yes

Notes - Fixed effect estimates. Model A: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model B: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers with different linguistic background and the number of native workers and foreign workers with the same linguistic background by cell. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.C.16: Estimated coefficients for nationality groups - without Eastern European countries

	Model A			Model B			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of hours worked	-0.058	-0.103***	-0.010	-0.136**	-0.152***	-0.102*	-0.002	0.004	0.014
	(0.03)	(0.01)	(0.05)	(0.04)	(0.04)	(0.05)	(0.01)	(0.01)	(0.03)
Observations	114	114	114	114	114	114	227	227	227
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	No	No	No	Yes

Notes - Fixed effect estimates. Model A: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model B: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers with different linguistic background and the number of native workers and foreign workers with the same linguistic background by cell. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Table 2.C.17: Estimated coefficients for nationality groups - without highly educated workers

	Model A			Model B			Model C		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of hours worked	-0.076	-0.110***	-0.072***	-0.147***	-0.159***	-0.105***	-0.021	-0.028**	0.035**
	(0.04)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	72	72	72	72	72	72	143	143	143
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time by education FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time by experience FE	No	No	Yes	No	No	Yes	No	No	Yes
Time by linguistic back. FE	No	No	No	No	No	No	No	No	Yes

Notes - Fixed effect estimates. Model A: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Model B: Group fixed effects are the interaction of education and experience fixed effects. The estimates are weighted by the ratio between the number of foreign workers with different linguistic background and the number of native workers and foreign workers with the same linguistic background by cell. Model C: Group fixed effects are the interaction of education, experience and linguistic background fixed effects. The estimates are weighted by the ratio between the number of foreign workers and the number of native workers by cell. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust and clustered at group level.

Chapter 3

The role of Chinese import competition in the employment of migrant workers

3.1 Introduction

An increase in the competition faced by firms on the final product market can have severe consequences on employment. The decrease in revenues may force firms to downsize their workforce. However, relatively little attention has been paid to the consequences that these changes may have on the nationality of workers employed. In the neoclassical literature changes in the economic environment do not differentially affect the employment of native and foreign workers. Nonetheless, if foreign workers are not perfect substitutes for native workers, this may not necessarily be the case. As a result, whether a shock to the product market increases or decreases the share of foreign workers employed may have very different consequences. If the employment of foreign workers decreases more than the employment of native workers, foreign workers may cushion the negative occupational effects for native workers. Alternatively, if the employment of foreign workers decreases less than the employment of native workers, the anti-immigration sentiments typically observed during economic downturns could intensify.

This paper attempts to tackle this issue. To identify the impact of changes in product market conditions on the nationality of workers employed, I follow the empirical strategy developed by Autor et al. (2013). They exploit the upsurge of China as a world leading manufacturing exporter in the early 2000s. In that period, China experienced a dramatic increase in its competitive advantage in the production of labor intensive goods. This is due to a number of factors, such as the modernization of the Chinese industrial structure and the expansion of global trade. As a consequence of this rise, the manufacturing industries of several developed countries faced an increase in competition from Chinese imported products. As widely discussed in the literature, in the US the competitive pressure from Chinese imported products triggered a substantial decrease in the manufacturing sector employment (see Acemoglu et al., 2016; Pierce and Schott, 2016; Autor et al., 2014, 2013). Also, it induced an increase in the offshoring of production tasks and an increase in the capital intensity of goods produced (Pierce and Schott, 2016; Bernard et al., 2006; Bustos, 2011).

Given the nature of the shock, the empirical analysis focuses on the US manufacturing sector. This is because the manufacturing sector has been the most directly affected by the increase in Chinese import competition. In addition, to do not confound the impact of Chinese import competition with the effects of the Great Recession, the empirical analysis is limited to 2007. As in Autor et al. (2013), this paper exploits the geographic concentration of industries. If more affected industries are more concentrated in some specific areas, it is possible to exploit the geographical variation in Chinese import exposure to identify the impact on employment composition. To avoid possible endogeneity between import competition and nationality of workers employed, Chinese import penetration in the US is instrumented with Chinese import penetration in other high income countries.

Overall, there are two mechanisms in which economic downturns may affect the nationality of workers employed. First, if foreign and native workers are imperfect substitutes and specialize in different occupations, the increase in competition from China should decrease the employment in industries more intensive in similar occupations. Since foreign workers are more likely to specialize in manual tasks (see for example Peri and Sparber, 2009), they may suffer relatively more the increase in the international trade of labor intensive goods from China. A second mechanism involves labor market frictions. If wages are paid below the marginal productivity, an increase in product market competition will induce firms to retain workers with greater value-for-money. If foreign workers face stronger labor market frictions (e.g. lower outside opportunities, lower bargaining power, etc.) and are more likely to accept lower wages for a given productivity level (or same wage for a larger productivity level), firms facing negative shocks in the product market may decide to retain more foreign workers.

The results show that the share of foreign workers employed increases in areas more exposed to Chinese import competition. This effect is stronger for foreign workers who have been in the US for a long time (more than 15 years) and for Asian and South and Central American workers. Interestingly, the increase in import competition does not alter task specialization. If anything, the decline in manual tasks is concentrated among native workers, who were already less specialized in those tasks. This suggests that task specialization is not the main channel through which the increase in import competition affects the employment of native and foreign workers. To indirectly test for differential labor market frictions, I exploit data on industry characteristics. Overall, foreign workers are more concentrated in more productive industries, suggesting that differences in the labor market may be the prevalent channel influencing the results.[1]

This paper exploits an international trade shock to relate the conditions faced by firms in the product market to the nationality of workers employed. In so doing, it adds to several strands of the literature. First of all, it adds to the migration literature. This literature mainly focuses on the supply impact of migration on labor markets (Dustmann et al., 2017; Ottaviano and Peri, 2012; Borjas and Katz, 2007; Borjas, 2003; Card, 2001 among the others). Nevertheless, there is a strand of the migration literature considering the role of labor demand on the employment of migrant workers.[2] However, while descriptively examining how labor demand can influence migration inflows, this literature does not attempt to quantify the relationship between the market conditions faced by the firms and the demand for migrant workers. This paper represents a novel extension of the migration literature in this respect.

Second, it adds to the literature on the impact of international trade on labor markets. Papers in this literature tackle this issue either calibrating theoretical models (as in Dix-Carneiro, 2014, Caliendo et al., 2015, Kambourov, 2009, Cosar, 2013) or implementing reduced form identification strategies exploiting structural breaks in trade policy (as in Autor et al., 2013, Acemoglu et al., 2016, Pierce and Schott, 2016, Hakobyan and McLaren, 2016, Dix-Carneiro and Kovak, 2015). However, this literature does not usually consider the impact of trade liberalization on the nationality of workers employed. This paper represents an innovative extension of this literature as well. Finally, providing evidence that labor market frictions may impact the nationality of workers employed, this paper indirectly adds to the literature on labor market frictions.

The remaining of the paper is structured as follows. The following section introduces the empirical strategy, discusses the main identification issues and describes the possible mechanisms influencing the results. Then, Section 3.3 and 3.4 discuss the data and the main findings. Finally, Section 3.5 concludes.

3.2 Empirical strategy and possible mechanisms

In the early 2000s the productivity of Chinese manufacturing firms dramatically increased. In this period China underwent profound reforms and shifted towards a market economy. At the same time, it entered some international agreements (e.g. WTO) to decrease trade barriers and foster

[1]This is in line with the findings in Mitaritonna et al. (2017) and Peri (2016, 2012) suggesting that foreign workers increase firm productivity in the destination countries.

[2]This literature can be traced back to Piore (1979).

international trade. Given the size and the structure of the Chinese economy, China acquired a strong competitive advantage in the production of labor intensive goods. As documented by Autor et al. (2013), this resulted in large employment losses in the competing US industries. In this paper, I replicate their identification strategy to investigate whether this startling change in international trade patterns affected the nationality of workers employed in the US manufacturing sector.

3.2.1 Empirical strategy

Different industries are typically concentrated in different geographic areas. Autor et al. (2013) exploit the geographic variation in industry concentration to evaluate the impact of Chinese competition on US manufacturing employment. They construct a measure of import penetration according to a simple model of international trade. Their theoretical framework does not consider different types of labor aggregates, but can be extended to account for native and foreign workers. Thus, I can adopt their same measure of import exposure, namely:

$$IP_{ht} = \sum_{j} \frac{L_{hjt}}{L_{jt}} \frac{M_{jt}}{L_{ht}} \tag{3.1}$$

where M_{jt} is the value of imports from China in industry j at time t, while L_{ht}, L_{jt}, L_{hjt} are respectively employment aggregates by commuting zone, industry and commuting zone and industry.[3] In words, they project the value of national imports at regional level weighting import values by the share of industry employment in each commuting zone and normalizing by the overall commuting zone employment. Then, weighted imports are aggregated at commuting zone level summing over industries. The main difference between the measure of import penetration in this paper and the one used by Autor et al. (2013) is that they adopt first differences in import exposure, while for the nature of the data I exploit in the empirical exercise, I consider import levels.

Overall, the regressions estimated in this paper have the form:

$$Y_{iht} = \lambda_t + \beta IP_{ht} + \gamma X_{iht} + \delta_h + \alpha + \varepsilon_{iht} \tag{3.2}$$

where Y_{iht} is a dependent variable for individual i in commuting zone h at time t and IP_{ht} is the constructed measure of import penetration in Equation (3.1). X_{iht} is a set of individual level controls, λ_t are time fixed effects, δ_h are commuting zone fixed effects and α is the constant. In the main specification of interest, Y_{iht} is a dummy variable equal to 1 for foreign workers. Since the explanatory variable of interest IP_{ht} is at commuting zone level, the estimated β coefficient can be interepreted as the impact on the share of foreign workers employed. Thus, a positive β coefficient suggests that an increase in import exposure, and thus in competition, increases the share foreign workers employed. A negative β coefficient suggests the opposite.

[3]Commuting zones are aggregates of counties with strong commuting ties.

3.2.2 Identification issues

Nevertheless, import exposure may be correlated with unobserved factors influencing employment and workers' nationality. Also, the increase in Chinese import exposure may have been anticipated by workers and firms, which could have changed their behaviour accordingly. To avoid possible bias, Autor et al. (2013) instrument Chinese import exposure in the US with Chinese import exposure in other high income countries. While imports from China should be positively correlated across high income countries, imports from other countries are unlikely to be correlated with employment in the US manufacturing sector. In this paper, the first stage of 2SLS is the same as in Autor et al. (2013). The exclusion restriction requires that changes in import exposure in other high income countries do not affect workers' nationality in the US manufacturing sector. Indeed, given that import exposure is likely to be positively correlated across high income countries, an increase in import exposure in the US is unlikely to induce large shifts of migrants towards similarly affected countries. Moreover, migrants deciding to move to the US face large relocating costs in changing their destination to Europe, Japan or Australia, making such a change quite unlikely.[4] Direct Chinese migration flows to the US are also quite unlikely to influence the results, since Chinese migration flows to the US are relatively scarce and, if anything, should decrease with the increase in international trade between China and the US.

Thus, the instrument is constructed as:

$$\mathcal{IP}_{ht} = \sum_j \frac{L_{hjt-1}}{L_{jt-1}} \frac{\mathcal{M}_{jt}}{L_{ht-1}} \tag{3.3}$$

where $\mathcal{M}_{jt}$ are imports from China to Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Employment aggregates are lagged to avoid the possibility of anticipated changes in Chinese import exposure affecting contemporaneous labor aggregates.

Another threat to the identification strategy may come from demographic trends. If the population of foreign workers is growing faster than the population of native workers and these trends are reflected by employment patterns, an increasing share of foreign workers employed may be due to the growing share of foreign population with respect to native population. However, this is not necessarily the case. Figure 3.1 shows the share of foreign workers in 2000 and 2007 across all economic sectors.[5] Even though the share of foreign workers is increasing in all economic sectors, the share of foreign workers among the unemployed and the inactive individuals is fairly stable. This suggests that the share of foreign workers employed does not rise uniformly in the economy

[4]Notice that a large shift in migration flows in response to the increase in import competition would also affect the exclusion restriction in the Autor et al. (2013) framework.

[5]Data are drawn from Census and American Community Survey and individual observations are aggregated according to personal weights.

and demographic effects are not likely to drive the results. Moreover, demographic trends should be accounted for by commuting zone and year fixed effects.

3.2.3 Possible mechanisms

There are two main channels through which an increase in import competition can affect the nationality of workers employed. First, the effect may take place through a shift in the tasks accomplished by workers. According to the baseline Heckscher-Ohlin theorem applied to the international trade of goods between China and the United States, if China gains a stronger competitive advantage in the production of labor intensive goods, the United States will specialize in the production of capital intensive goods. If foreign and native individuals working in the US do not specialize in particular occupations, an international trade shock should not impact the proportion of foreign workers employed. However, as Peri and Sparber (2009) show, foreign and native workers are likely to specialize in different occupations. Particularly, since native workers have superior linguistic abilities (Lewis, 2013; Gentili and Mazzonna, 2017), they are more likely to specialize in communication intensive tasks, while foreign workers are more likely to specialize in manual and cognitive tasks. Thus, assuming that manual tasks are more concentrated in industries producing labor intensive goods, an increase in the Chinese comparative advantage in labor intensive goods should disproportionately affect foreign workers, reducing their employment.

However, there is a second possible channel through which an increase in competition from China may induce a shift in the proportion of native and foreign workers employed. If there are frictions in the labor market, wages are paid below the marginal productivity of workers. Within this framework, an increase in product market competition may induce firms to retain workers with larger value-for-money. If foreign workers have lower bargaining power in setting wages than native workers or different value functions (for instance, foreign workers may have lower outside opportunities, discount factors or probability of receiving a job offer), an increase in product market competition will increase the share of foreign workers employed. Models of job search considering different value functions for native and foreign workers have been developed by Eckstein and Wolpin (1999), Battisti et al. (2017) and Chassamboulli and Palivos (2013). Calibrating their models, they find that differences in labor market frictions can account for wage and employment differentials.

3.3 Data

The main sources of data are the 1990 and 2000 Census waves and the American Community Survey (ACS) between 2005 and 2007. The time span stops to 2007 to do not confound the effects of the increase in Chinese import competition with the effects of the Great Recession. Before 2007, the choice of the years is dictated by data availability. Commuting zones are the most suitable geographical units to define local labor markets because they are defined in terms of commuting ties. However, they are not directly reported in ACS and Census data. Individuals in 1990 and 2000 Census and in 2005-2007 ACS are geographically identified according to county, public use microdata areas (PUMA) and state. However, counties without a sufficient number of individuals are not reported. PUMAs are geographical units used in the sampling design of Census and ACS and are defined in terms of counties. Since also commuting zones are defined as aggregations of counties, each individual can be assigned to a commuting zone according to the county of residence or the PUMA of residence. ACS data between 2001 and 2004 do not report PUMAs and individuals cannot be related to commuting zones. The detailed attribution procedure for the available years is described in Appendix 3.A.1.

In the empirical analysis, individual data are complemented by data on Chinese import exposure from Autor et al. (2013), data on task intensity from the O*NET online database and data on industry characteristics from the NBER-CES Manufacturing Industry Database by Becker et al. (2013). Merging these datasets requires some harmonization of industry, commuting zone and occupation codes. A detailed description of these procedures can be found in Appendix 3.A.

3.3.1 Census and ACS data

Census and ACS data provide individual level information on the nationality of workers, the industry of work, occupations and annual earned income. While the nationality of workers, the broad education group and the logarithm of annual income are exploited as dependent variables, all the other characteristics are used as control variables in the individual level regressions. In the empirical analysis, foreign workers are defined according to the variable *Citizen*. Following the literature (see for example Ottaviano and Peri, 2012), naturalized citizens and non-citizens are classified as foreign workers, while individuals born abroad of American parents are classified as natives. Control variables are dummy variables for education attainment, marital status, gender, broad occupation category, 4-digit industry codes.[6] Also, I control for age and Siegel occupational prestige score.

I restrict the sample to employed workers aged 18 or more with remunerated labor the week before and not self-employed. Then, I only retain individuals working in the manufacturing sector and drop individuals with missing industry codes. After this process, the overall sample size

[6] Dummy variables for education attainment are constructed according to the variable *Educ*. Dummy variables for broad occupation categories are defined according to the variable *occ1990*. Particularly, I control for 6 occupation categories: managerial and professional specialty occupations; technical, sales, and administrative support occupations; service occupations; farming, forestry, and fishing occupations; precision production, craft, and repair occupations; operators, fabricators, and laborers. More details are reported in Appendix 3.A.1. Dummy variables for 4-digit industries are constructed as described in Appendix 3.A.1.

amounts to roughly 2.3 million observations. Table 3.1 shows some descriptive statistics comparing the sample of workers in the manufacturing sector to the whole sample of workers. On average, people working in the manufacturing sector are more likely to be men, married, less educated and to be employed as operators and laborers. Also, the average real wage per year is larger in the manufacturing sector. To investigate the composition of foreign workers employed, I consider their place of birth and years since arrival in the United States. Even though the share of foreign workers in the manufacturing sector is slightly larger with respect to the overall sample, the composition of foreign workers is fairly similar between the two samples, both in terms of place of birth and years in the United States.

To provide a grasp of the changes in the nationality composition of manufacturing employment, Figure 3.2 shows the trends between 2000 and 2007 in the absolute number of workers by nationality and education. Each trend is reported on a different graph because of the large differences in scales. The two graphs on the left depict the trends between 2000 and 2007 for highly and low educated native workers. The decline in employment has been sharper for low educated native workers, and around 20% of their jobs went lost. Similarly, the employment of highly educated natives declined by 7%. On the contrary, low educated foreign workers did not face a similar decline, even though their employment has been more volatile over time. The employment of highly educated foreign workers has been slightly increasing (by about 100,000 jobs, 15% of the initial number). Thus, the increasing share of foreign workers shown in Figure 3.1 seems to be related to greater layoffs among native workers.

3.3.2 Other data sources

To construct the two measures of commuting zone import exposure defined in Equations (3.1) and (3.3), I exploit data on import levels from the publicly available dataset by Autor et al. (2013). Employment weights are computed from Census and ACS data, weighting each individual observation by personal weights and aggregating them by commuting zone, industry or both.[7] Figure 3.3 shows the evolution of average import exposure in the US and in other high income countries. It is possible to see how import exposure magnified over time, especially after 2000. Also, the two variables show a similar trend, suggesting a large positive correlation.

To explore possible changes in task specialization induced by the increase in Chinese competition, I add information on occupation tasks from the O*NET database. In this database, importance scores of each task for each occupation are constructed according to expert interviews.

[7] Note that the instrumental variable in Equation (3.3) is constructed with lagged employment aggregates. Thus, to compute lagged labor aggregates for 1990, I exploit the 1980 Census.

Occupations are classified according to the Standard Occupational Classification (SOC) system and the importance of each task is rated between 0 and 100. Following Peri and Sparber (2009), I construct the importance scores for manual, cognitive and communication tasks averaging the importance scores of the underlying abilities. The underlying abilities are listed in Appendix 3.A.3.

Finally, to provide some descriptive evidence about possible differences between native and foreign workers on the labor market, I also add industry information from the NBER-CES Manufacturing Industry Database, a panel dataset following industry characteristics over time. The NBER-CES Manufacturing Industry Database is constructed combining information from the Economic Census and the Annual Survey of Manufactures and spans between 1958 and 2011. Industry codes are harmonized and coded according to 6-digit NAICS. For each industry and year, it reports data on number of workers employed, number of workers in production, value of shipments, value added, cost of materials, cost of energy and other fuels, wages, investments in capital, inventories and real capital stock. Since industry codes in the ACS and Census data are reported with a different number of digits, I harmonize them according to 4-digit NAICS codes as described in Appendix 3.A.1 and collapse the information at industry level reported in the NBER-CES Manufacturing Industry Database at 4-digit NAICS codes.

After attributing industry characteristics to each individual, I exploit information about average productivity, industry concentration and share of workers not in production. Productivity is computed as the ratio between value added and employed workers and measures the average ability of workers to produce value added. Industry concentration is computed normalizing value added by value of shipments and measures the degree of monopolistic concentration of an industry. Indeed, the smaller the incidence of value added on revenues, the stronger the competition in the industry. On the contrary, the larger the incidence of value added on revenues, the stronger the monopolistic concentration of the industry. Finally, since the NBER-CES Manufacturing Industry Database separately reports the number of workers employed in production, the share of workers not in production is simply the ratio between workers not in production and employment. This ratio measures the importance of production tasks by industry and may provide an indirect measure of their offshoring.

3.4 Results

3.4.1 Employment of foreign workers

Table 3.2 reports the impact of an increase in import exposure on the share of foreign workers employed. Estimates in Column 1 are obtained controlling for year, industry and commuting zone fixed effects. To control for different trends over time in different states and industries, Column 2 adds state by year fixed effects, Column 3 industry by year fixed effects, and Column 4 both state by year and industry by year fixed effects. In all the specifications, the coefficients of interest are always positive and significant, suggesting that commuting zones more exposed to Chinese import competition show a larger share of foreign workers employed. This is also confirmed by 2SLS results, which are qualitatively similar to OLS estimates, even though larger in magnitude. As conjectured in Section 3.2, the instrumental and the instrumented variables are positively correlated, with a statistically significant first stage coefficient of 0.83 for the baseline estimate in Column 1.

The overall effect of the increase in import competition is quite large. In the baseline specification in Column 1, a standard deviation increase in import competition exposure increases the share of foreign workers employed by 3%, which corresponds to an increase in the mean share of foreign workers of 18%. Even in the most demanding specification in Column 4, a standard deviation increase in import exposure increases the mean share of foreign workers of 14%. Notice that the results are not very different across the four specifications, and the adjusted R-squared does not improve much adding controls. Thus, in the following I only control for year, industry and commuting zone fixed effects.

Since the empirical strategy adopts the dummy variable for foreign workers as dependent variable, the potential underreporting of foreign workers in Census and ACS data may lead to sample selection bias. This concern is mitigated by the choice of the data sources, since Census and ACS also include unauthorized immigrants. Nevertheless, as discussed by Card and Lewis (2007), in 1990 the undercount of unauthorized immigrants was larger than in 2000.[8] For this reason, Table 3.B.1 reports the results excluding 1990 from the estimates. The resulting coefficient is smaller in magnitude, but still consistent with the main estimates.[9] Overall, estimates in Table 3.2 seem to be robust to potential sample selection bias.

Now, it is interesting to understand what types of migrant workers are more concentrated in more exposed commuting zones. Table 3.3 presents the results by migrants' place of birth, while Table 3.4 shows the results by time spent in the United States.[10] Migrants in more exposed commuting zones are more likely to come from Central and South America and Asia and are less likely to come from Europe. In addition, migrants in more exposed commuting zones are the most assimilated in the United States, since they are more likely to have been in the United States for more than 15 years and less likely to have been in the United States for less then 5 years or between

[8]The undercount of Mexican workers is around 20% in 1990. From 2000 on, the undercount of unauthorized foreign workers drops to 10%.

[9]Recalling Figure 3.3, information about 1990 is important to increase the variation over time in import exposure.

[10]Time spent in the United States is computed according to the declared year of arrival.

5 and 10 years. These results are quite intuitive, since more exposed commuting zones are less likely to attract recent migrant workers.

An interesting exercise is to decompose the impact of Chinese import competition on the share of foreign workers according to the education attainment. The results reported in Table 3.5 show that the effect is spread on both highly and low educated workers.[11] Specifically, the effect is larger among highly educated workers. Indeed, a standard deviation increase in import penetration increases the mean share of highly educated workers by 27%. The corresponding increase in the mean share of low educated workers is 15%.

3.4.2 Discussion of the mechanisms

As previously mentioned, there are two possible mechanisms through which changes in the structure of the product market can affect the national composition of workers employed. The first mechanism consists in the specialization of native and foreign workers in different tasks. Since foreign workers are more likely to be employed in manual tasks, an increase in import competition in labor intensive products should decrease the employment of migrant workers more than the employment of native workers. The results of Table 3.2 suggest that this is not the main mechanism at work in this context. However, to further confirm this intuition, Table 3.6 reports the impact of an increase in import exposure on the average importance of manual, cognitive and communication tasks. Overall, the importance of manual tasks is decreasing in more exposed commuting zones. A standard deviation increase in import penetration decreases the average importance of manual tasks by 0.2%. However, cognitive and communication tasks do not seem to be affected. Table 3.B.2 provides the same estimates by nationality. If anything, the reallocation in tasks seems to be concentrated among native workers. Interestingly, this happens even though the average importance of manual tasks is smaller for natives and the average importance of communication tasks is larger. Thus, even though some task reallocation can still be in place, it is not the main channel through which an increase in import competition from China affects the nationality of workers employed.

The second channel through which the increase in import competition may have impacted the employment of foreign workers is related to different labor market frictions for native and foreign workers. If foreign workers are paid less for the same tasks or if they are more productive for the same salaries, firms will tend to retain more foreign workers than native workers. This may be the case if foreign workers face different outside opportunities, have lower bargaining power or have different employment opportunities. Testing directly for such characteristics requires calibrating a

[11] Highly educated workers are defined as workers with at least some college education, while low educated workers are defined as workers with high school diploma or less.

search model. Such an exercise is beyond the scope of this paper and is accurately done in Battisti et al. (2017) for 20 developed countries. However, to provide some more descriptive insights on this channel, I exploit the information from the NBER-CES Manufacturing Industry Database to check whether there are observed differences in the industries of work of native and foreign workers.

Table 3.7 reports sample averages by industry characteristics and nationality of workers, weighting by individual personal weights. Industry productivity, industry concentration and share of workers not in production are drawn from the NBER-CES Manufacturing Industry Database. The logarithm of annual wages, instead, is based on the salary reported in the ACS and Census data. Since the increase in foreign workers seems to be concentrated among foreign workers arrived in the United States more than 15 years ago, Columns (2) and (3) report average characteristics separately for them. On average, foreign workers are more concentrated in more productive industries. Interestingly, there can be different mechanisms at work for recent foreign workers and non-recent foreign workers, both leading to the same results. On the one hand, recent foreign workers are paid around 11,000 dollar per year less than other workers. On the other hand, non-recent foreign workers are more concentrated in more productive industries. In both cases foreign workers are a better investment for firms. Notice that the greater concentration of foreign workers in more productive industries holds regardless of Chinese import penetration. In a further check (not reported) I consider individuals living in the 10% of commuting zones more exposed to Chinese import competition and the 10% of commuting zones less exposed in 1990 and 2007. In all cases, foreign workers are more concentrated in more productive industries than native workers.

3.4.3 Other dependent variables

To provide a broader picture of the changes in workforce composition induced by the increase in Chinese import penetration, Table 3.8 and 3.9 show the impact on wages and on the share of highly educated workers employed. In Table 3.8 results are reported separately by nationality and education. Overall, wages are increasing in the manufacturing sector. This is in line with the results by Autor et al. (2013), who find negative wage effects on the overall economy, but positive and statistically non-significant wage effects in the manufacturing sector. This is probably due to the fact that firms only retain more productive workers or that only more productive firms are able to survive to Chinese import competition. Particularly, the increase in wages is concentrated among highly educated workers. A standard deviation increase in import penetration increases the average log wages of highly educated native and foreign workers by 0.2%, which roughly corresponds to an increase in 800 dollars per year. Results using weekly wages rather than annual wages are qualitatively similar (Table 3.B.3).

In addition, the jobs lost because of Chinese import competition are concentrated among lower paid workers. Table 3.9 shows the impact of Chinese import competition on the share of highly educated workers. Overall, a standard deviation increase in import penetration increases the mean share of highly educated workers of 0.1%. Distinguishing by nationality, the effect seems to be concentrated among natives, although it is quite small in magnitude. This reinforces the previous findings on wages, suggesting that the readjustment is mainly concentrated among low educated workers.

3.5 Conclusion

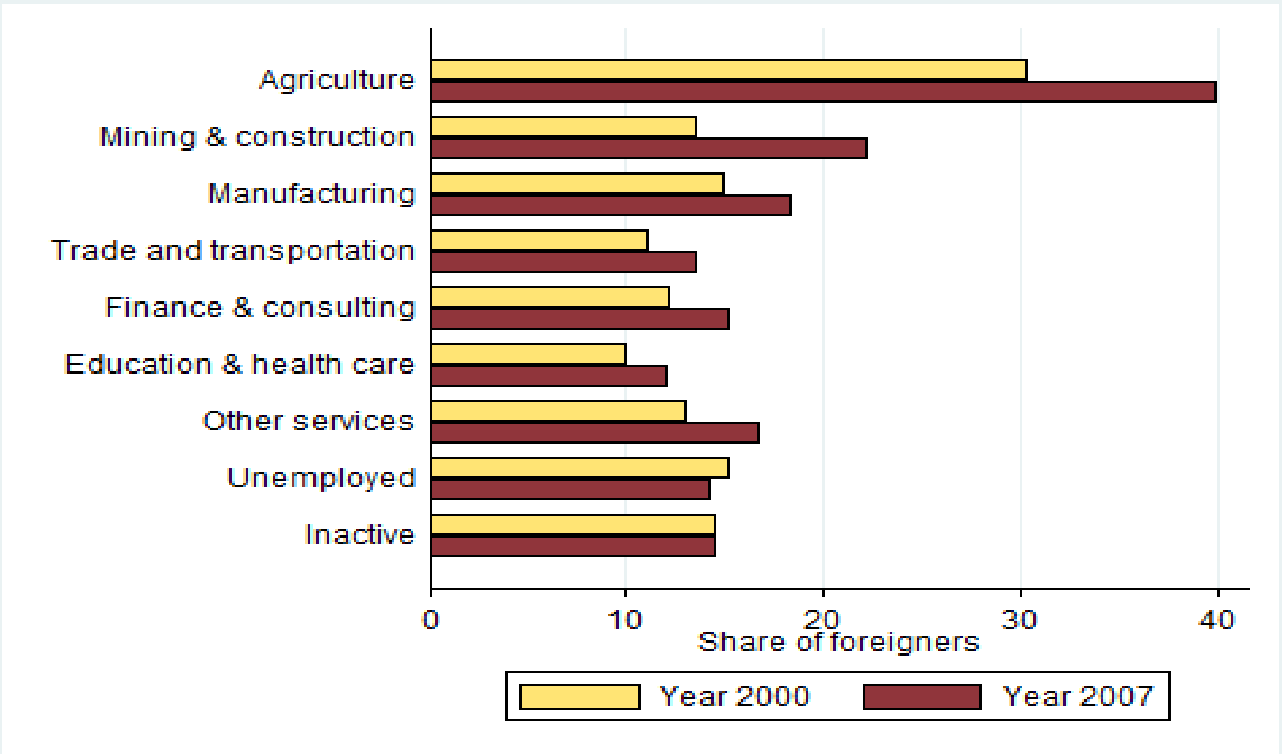
This paper investigates whether changes in the economic structure of product markets affect the nationality of workers employed. The empirical strategy exploits exposure to Chinese import competition between 1990 and 2007. As in Autor et al. (2013), I construct a measure of regional exposure to Chinese import competition. To deal with the potential endogeneity of import exposure with respect to employment, imports from China to the US are instrumented with imports from China to other eight high income countries. While the decrease in US manufacturing employment is widely documented in the literature, in investigating the nationality of workers retained by the manufacturing industries, this paper finds that the share of foreign workers employed increases in areas more exposed to Chinese import competition.

There are two possible mechanisms through which a shock to the product market can influence the employment of migrant workers: task specialization and differential labor market frictions. Overall, areas more exposed to Chinese import competition show a little decrease in manual intensive tasks. However, the effect is small and when decomposing between native and foreign workers, it seems to be concentrated among native workers. This suggests that task specialization is not the main mechanism through which the labor market readjusts to the shock. Considering average industry characteristics by workers' nationality, foreign workers are concentrated in more productive industries with respect to native workers. Thus, firms surviving to Chinese import competition probably attempt to decrease their labor costs retaining the more productive workers, i.e. foreign workers. Interestingly, this paper also shows that migration has a long standing impact, since foreign workers in the US for more than 15 years seem to maintain their greater productivity.

These results have strong policy implications. First, they are relevant for the design of policies altering the competitive structure of product markets. Indeed, if the increase in trade following a market liberalization does not improve the productive capacity of the economy, firms may not only be forced to downsize their employment stock, but also to readjust towards specific components of their workforce. In the case of foreign workers, this could exacerbate anti-immigration feelings in the native population, raising social tensions. Second, these results can be relevant for the design of migration policies, since firms are benefiting from the employment of migrant workers. Indeed, in times of increasing competitive pressures, the employment of migrant workers allow firms to decrease their marginal cost of labor and to maintain their competitiveness on the final product market. The employment of migrant workers may not only be a source of short term profit for firms, but can also insure them against future negative shocks. In this respect, migration policies may have lasting consequences in the long run, since foreign workers maintain their greater productivity even after being assimilated in the destination country. Whether it is better favoring firms or protecting native workers is an open political issue.

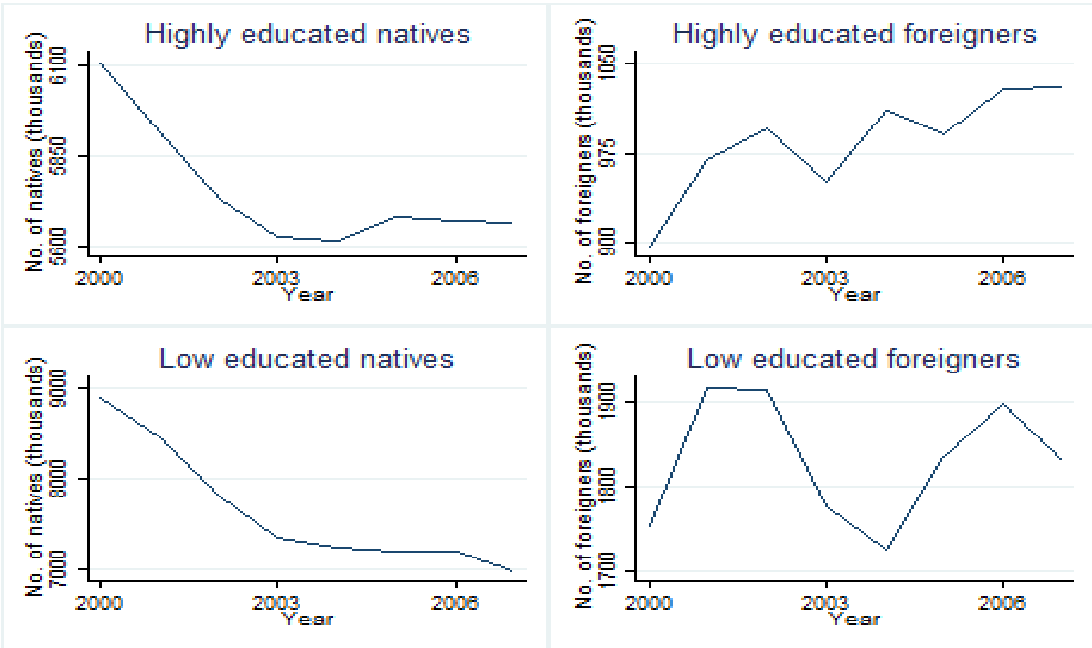
Before concluding, it is worth emphasizing that these results are short term consequences of an increase in product market competition. In the long run, the economy can readjust and reabsorb the displaced native workers. Moreover, the evidence presented in this paper may be contingent to the peculiar economic context. Nevertheless, policy makers should keep in mind these dynamics as possible outcomes of an increase in competitive pressures.

Figure 3.1: Share of foreign workers by sector



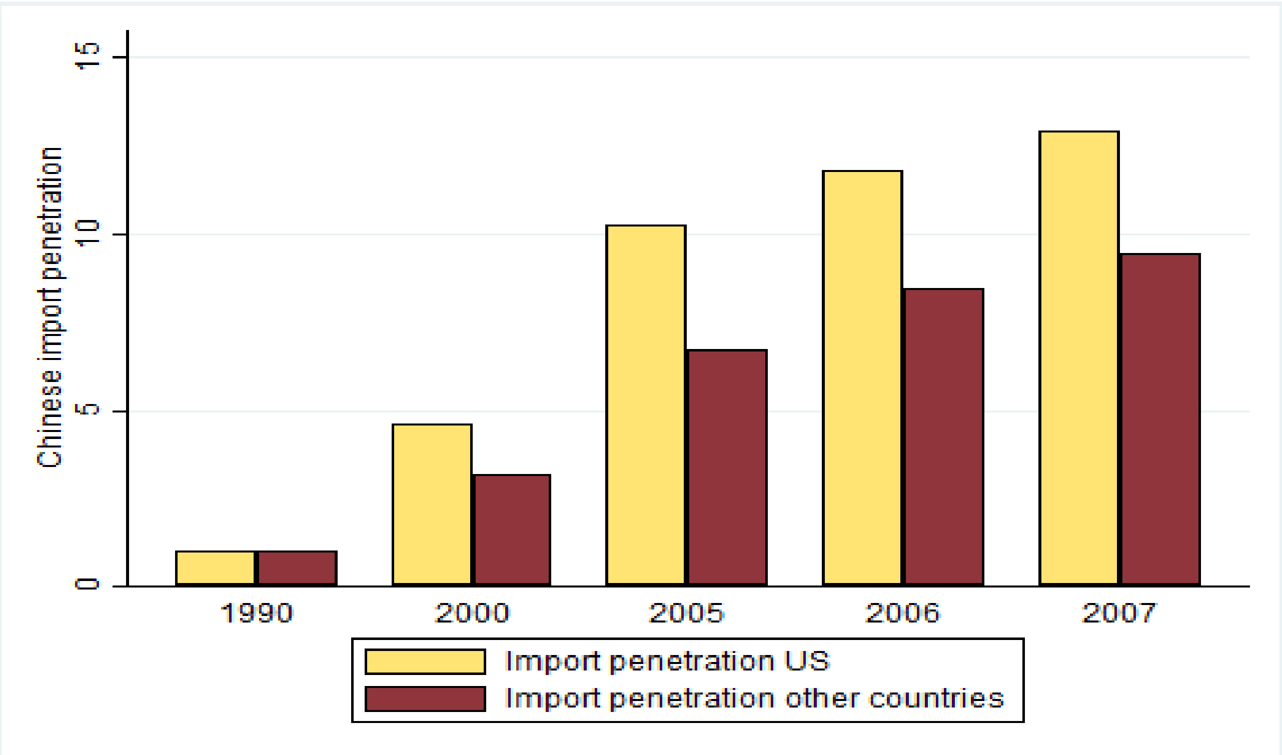
Notes - Foreign workers are defined as naturalized citizens and non-citizens. All the other individuals are regarded as natives. Sectors are defined according to the first figure of NAICS codes. "Agriculture" includes individuals working in industries beginning with 1, "Mining and construction" includes individuals working in industries beginning with 2, etc. Other services includes industries beginning with 7 ("Arts, entertainment, and recreation" and "Accommodation and food services"), 8 ("Other services"), and 9 ("Public administration"). Shares are computed weighting each observation by personal weights. Individuals below 18 years old are excluded from the sample.
Sources: Census and ACS - years 2000 and 2007.

Figure 3.2: Trends in manufacturing sector employment by nationality and education



Notes - The sample is restricted to employed workers in the manufacturing sector, older than 18, with remunerated work the week before and not self-employed. Foreign workers are defined as naturalized citizens and non-citizens. Numbers of workers are obtained weighting each observation by individual personal weights and are reported in thousands.
Sources: Census and ACS - years 2000-2007.

Figure 3.3: Average Chinese import penetration by year



Notes - Chinese import penetration in the US and in other high income countries over time. The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Chinese import penetration in the US is computed as in Equation (3.1). Chinese import penetration in other high income countries is computed as in Equation (3.3). Employment weights in Equation (3.3) are lagged one period. However, plotting unweighted import values in the US and in other high income countries gives a similar graphical result. Individual data are aggregated using personal weights.
Sources: Import data from Autor et al. (2013) - years 1990, 2000, 2005-2007.

Table 3.1: Comparison of individual characteristics across samples

	Manufacturing sector	Whole sample
Share men	0.69	0.53
Share married	0.62	0.55
Share some college education	0.42	0.54
Age	41	40
Average income	37,922	35,719
Share foreign born	0.16	0.14
Share foreign born from South and Central America	0.09	0.07
Share foreign born from Asia	0.05	0.04
Share foreign born from Europe	0.02	0.02
Share foreign born from Africa	0.003	0.005
Share foreign born arrived less than 5 years ago	0.02	0.02
Share foreign born arrived btw. 5-10 years ago	0.03	0.03
Share foreign born arrived btw. 10-20 years ago	0.06	0.05
Share foreign born arrived more than 20 years ago	0.05	0.04
Siegel occupational prestige score	38	41
Managerial occupations	0.21	0.29
Technical, sale and administrative support	0.18	0.31
Service occupations	0.02	0.14
Precision production, craft and repair	0.18	0.10
Operators, fabricators, and laborers	0.41	0.14
Observations	2,284,550	14,068,573

Notes - The whole sample contains employed workers older than 18, with remunerated work the week before, not self-employed and with non-missing industry of work (NAICS). The sample for the manufacturing sector only contains individuals working in the manufacturing sector (NAICS beginning with 3). Occupational categories are defined according to 1990 Census Bureau classification scheme as reported in the ACS and Census variable *occ1990*. See footnote 6 for further details on occupational categories.
Sources: Census and ACS - years 1990, 2000, 2005-2007.

Table 3.2: Impact of exposure to Chinese import competition on the share of foreign workers

Column	(1)	(2)	(3)	(4)
		OLS estimates		
Import penetration	0.0034***	0.0019**	0.0032***	0.0018**
	(0.0005)	(0.0009)	(0.0005)	(0.0008)
		2SLS estimates		
Import penetration	0.0048***	0.0040**	0.0047***	0.0040**
	(0.0008)	(0.0017)	(0.0008)	(0.0016)
Individual level controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Commuting zone f.e.	Yes	Yes	Yes	Yes
State-year f.e.	No	Yes	No	Yes
Industry-year f.e.	No	No	Yes	Yes
Observations	2,284,550	2,284,550	2,284,550	2,284,550
R-squared	0.303	0.305	0.304	0.306
Kleibergen-Paap F	257	82	273	84
Mean foreign	0.16	0.16	0.16	0.16
Std. dev. import penetration	5.71	5.71	5.71	5.71

Notes - The dependent variable is a dummy equal to 1 for foreign workers. Foreign workers are defined as naturalized citizens and non-citizens. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.3: Impact of exposure to Chinese import competition on the share of foreign workers by place of birth

Column	South and Central America (1)	Asia (2)	Europe (3)	Africa (4)
		OLS estimates		
Import penetration	0.0021***	0.0020***	-0.0002**	0.0000
	(0.001)	(0.001)	(0.000)	(0.000)
		2SLS estimates		
Import penetration	0.0035***	0.0025***	-0.0005***	0.0000
	(0.001)	(0.000)	(0.000)	(0.000)
Individual level controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Commuting zone f. e.	Yes	Yes	Yes	Yes
Observations	2,284,550	2,284,550	2,284,550	2,284,550
R-squared	0.316	0.101	0.027	0.007
Kleibergen-Paap F	257	257	257	257
Mean dep. variable	0.09	0.05	0.02	0.003
Std. dev. import penetration	5.71	5.71	5.71	5.71

Notes - Dependent variables are dummies equal to 1 according to the continent of birth of foreign workers. Foreign workers are defined as naturalized citizens and non-citizens. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.4: Impact of exposure to Chinese import competition on the share of foreign workers by time of immigration

Column	≤5 years (1)	6-10 years (2)	11-15 years (3)	16-20 years (4)	21-25 years (5)	>25 years (6)
			OLS estimates			
Import penetration	-0.0011*	-0.0009	-0.0002	0.0010**	0.0011***	0.0033**
	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0004)	(0.0013)
			2SLS estimates			
Import penetration	-0.0018***	-0.0015*	-0.0006	0.0015***	0.0015***	0.0056***
	(0.0006)	(0.0009)	(0.0012)	(0.0004)	(0.0004)	(0.0019)
Individual level controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Commuting zone f. e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,284,550	2,284,550	2,284,550	2,284,550	2,284,550	2,284,550
R-squared	0.065	0.057	0.049	0.049	0.035	0.072
Kleibergen-Paap F	257	257	257	257	257	257
Mean dep. variable	0.03	0.03	0.03	0.02	0.02	0.03
Std. dev. import penetration	5.71	5.71	5.71	5.71	5.71	5.71

Notes - Dependent variables are dummies equal to 1 according to the time of arrival of migrant workers in the US. Foreign workers are defined as naturalized citizens and non-citizens. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.5: Impact of exposure to Chinese import competition on the share of foreign workers by education group

Column	Highly educ. (1)	Low educ. (2)
	OLS estimates	
Import penetration	0.0045***	0.0033***
	(0.0010)	(0.0007)
	2SLS estimates	
Import penetration	0.0059***	0.0051***
	(0.0006)	(0.0014)
Individual level controls	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Commuting zone f. e.	Yes	Yes
Observations	920,537	1,364,013
R-squared	0.160	0.407
Kleibergen-Paap F	228	255
Mean foreign	0.13	0.18
Std. dev. import penetration	5.98	5.49

Notes - The dependent variable is a dummy equal to 1 for foreign workers. Foreign workers are defined as naturalized citizens and non-citizens. Highly educated workers are workers with at least some college education, while low educated workers are workers with high school diploma or less. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.6: Impact of exposure to Chinese import competition on task intensity

Column	Manual (1)	Cognitive (2)	Communic. (3)
		OLS estimates	
Import penetration	-0.0118***	0.0010	0.0062**
	(0.0033)	(0.0038)	(0.0028)
		2SLS estimates	
Import penetration	-0.0108**	-0.0014	0.0019
	(0.0052)	(0.0044)	(0.0037)
Individual level controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Commuting zone f. e.	Yes	Yes	Yes
Observations	2,284,550	2,284,550	2,284,550
R-squared	0.868	0.804	0.787
Kleibergen-Paap F	257	257	257
Mean dep. variable	28.22	46.04	58.44
Std. dev. import penetration	5.71	5.71	5.71

Notes - Dependent variables are the average importance of manual, cognitive and communication tasks (detailed list in Appendix 3.A.3). Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.7: Average industry characteristics

	Natives	Foreigners <15 years in the US	Foreigners $\geq$ 15 years in the US
Column	(1)	(2)	(3)
Productivity (VA/emp)	196.81	253.17	277.73
Industry concentration (VA/revenues)	0.51	0.51	0.52
Share of workers not in production	0.31	0.31	0.33
Annual wages (in logarithm)	10.29	9.85	10.19

Notes - Productivity is computed as the ratio between inflation-adjusted value added and employment. Industry concentration is computed as the ratio between inflation-adjusted value added and value of shipments. Productivity, industry concentration and share of workers not in production come from the NBER-CES Manufacturing Industry Database. Value added, value of shipments, employment and share of workers not in production are assigned to each individual according to the 4-digit industry of work. The logarithm of annual wages comes from ACS and Census data. Averages are computed weighting each observation by personal weights.

Table 3.8: Impact of exposure to Chinese import competition on wages by education and nationality

	Foreigners		*Natives*	
	Highly educ.	Low educ.	Highly educ.	Low educ.
Column	(1)	(2)	(3)	(4)
		OLS estimates		
Import penetration	0.0054***	0.0022	0.0035***	0.0012
	(0.0014)	(0.0016)	(0.0010)	(0.0011)
		2SLS estimates		
Import penetration	0.0037*	0.0017	0.0039***	0.0004
	(0.0021)	(0.0019)	(0.0011)	(0.0014)
Individual level controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Commuting zone f. e.	Yes	Yes	Yes	Yes
Observations	99,470	181,425	821,067	1,182,588
R-squared	0.399	0.223	0.374	0.261
Kleibergen-Paap F	126	757	241	121
Mean dep. variable	10.54	9.73	10.59	10.05
Std. dev. import penetration	6.99	6.54	5.70	5.06

Notes - The dependent variables are the logarithm of yearly wages. Foreign workers are defined as naturalized citizens and non-citizens. Highly educated workers are workers with at least some college education, while low educated workers are workers with high school diploma or less. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.9: Impact of exposure to Chinese import competition on the share of highly educated workers

Column	All (1)	Foreign (2)	Native (3)
	OLS estimates		
Import penetration	0.0006***	0.0004	0.0001*
	(0.0002)	(0.0003)	(0.0000)
	2SLS estimates		
Import penetration	0.0010***	0.0005	0.0001***
	(0.0003)	(0.0005)	(0.0000)
Individual level controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Commuting zone f. e.	Yes	Yes	Yes
Observations	2,284,550	280,895	2,003,655
R-squared	0.974	0.911	0.991
Kleibergen-Paap F	257	363	171
Mean dep. variable	0.42	0.35	0.43
Std. dev. import penetration	5.71	6.71	5.35

Notes - Dependent variables are dummies equal to 1 if the worker has at least 1 year of college education. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Appendix

3.A Data, crosswalks and harmonization procedures

3.A.1 ACS and Census data

Occupation codes

Dummy variables for occupation categories are constructed according to the variable *occ1990*. Categories are constructed as follows:

- *Managerial and professional specialty occupations*: codes between 002 and 200;
- *Technical, sales, and administrative support occupations*: codes between 201 and 390;
- *Service occupations*: codes between 400 and 469;
- *Farming, forestry, and fishing occupations*: codes between 470 and 500;
- *Precision production, craft, and repair occupations*: codes between 501 and 700;
- *Operators, fabricators, and laborers*: codes between 701 and 900.

Industry codes

From 2000 on, industries are coded according to the North American Industry Classification System (NAICS) at different levels of precision.[12] To obtain homogeneous industry categories, I convert all the NAICS codes into 4-digit NAICS codes, retaining the first 4 digits of 5- and 6-digit NAICS codes, and randomly assigning 1-, 2-, and 3-digit NAICS codes to 4-digit NAICS subcategories. Industries in the 1990 Census, instead, are reported according to the Census industry classification system. 1990 Census industry codes are converted into NAICS codes through the concordance table provided by the Census Bureau.

Commuting zones

Since commuting zones are aggregations of counties with homogenous labor markets, assigning a commuting zone to each individual in the Census waves and in the ACS requires knowledge of the county of residence of the individual. Nevertheless, for privacy reasons, in the ACS and Cen-

[12]NAICS codes vary between 1 and 6 digits according to the precision of industry definition.

sus waves individual counties are only reported when the numerosity of individuals by county is sufficiently high. For the other observations, the smaller geographic unit available is the Public Use Microdata Area (PUMA). Thus, when counties are present, commuting zones are assigned according to the crosswalk between commuting zones and counties available in the David Dorn data page. If counties are not available, the procedure is slightly more complicated, since the borders of PUMAs are not perfectly overlapping with commuting zones. This means that the same PUMA can be split over different commuting zones and vice versa. The David Dorn data page also provides the necessary crosswalks between PUMAs and commuting zones.[13] These crosswalks are based on a probabilistic matching and provide employment weights indicating the share of the PUMA population that should be assigned to each corresponding commuting zone. Thus, when only PUMAs are available, individuals are randomly assigned to each commuting zone according to the probabilistic weights defined by Dorn.[14]

To compute lagged labor aggregates in Equation (3.3), I assign commuting zones to individuals in the 1980 Census as well. In the 1980 Census PUMAs are not defined, but there are other geographic units, county groups, that allow for the attribution of commuting zones to individuals. The appropriate crosswalk between 1980 county groups and commuting zones is still provided by David Dorn in his data page.

3.A.2 Data on import exposure

SIC-NAICS crosswalk for import data

Import data from Autor et al. (2013) are available from 1991 to 2007 and are provided according to the 1987 Standard Industrial Classification (SIC) codes. To convert SIC codes into NAICS codes, I use the SIC-NAICS crosswalk provided by David Dorn. However, since a NAICS code may overlap with more than one SIC code, I deterministically assign import values dividing the value of imports by the number of corresponding NAICS codes. Finally, I aggregate imports by 4-digit NAICS codes and attach them to individual observations.[15]

3.A.3 O*NET

Occupation codes

Occupation codes in the O*NET are reported according to the 2010 Standard Occupational Classification (SOC) version. Since occupations in the 2000 Census and ACS are reported according to

[13]Since PUMA codes are not consistent over time, two different crosswalks are provided for year 1990 and for years from 2000 on. These crosswalks have already been applied in Autor and Dorn (2013) and Dorn (2009).

[14]Following Autor et al. (2013), I remove from the sample individuals belonging to the commuting zones of Alaska and Hawaii.

[15]Individuals in the 1990 Census are assigned import levels of 1991.

the 2000 SOC version, I convert the 2010 SOC codes in the O*NET to 2000 SOC codes through the 2000-2010 SOC crosswalk provided by the Bureau of Labor Statistics.

Then, since occupations in the 1990 Census are not reported according to SOC, I perform some additional steps. The IPUMS website provides a crosswalk between 2000 occupation codes and SOC codes for the 2000 Census. Thus, to assign 2000 SOC codes to individuals in the 1990 Census, I first convert 1990 occupation codes to 2000 occupation codes and then 2000 occupation codes to 2000 SOC codes. Particularly, I uniform 1990 occupation codes to 2000 occupation codes through the crosswalk between *occ1990* and contemporary occupation codes provided by the IPUMS website. If an occupation code in 1990 corresponds to more than one occupation code in 2000, I randomly assign individuals to the corresponding 2000 occupation codes. Finally, I exploit the occupation descriptions to manually assign individuals in occupations without direct correspondence. This manual and random assignment only involved 6% of individuals working in the manufacturing sector in the 1990 Census. To complete the matching, since SOC occupations in ACS and Census waves are not always reported according to 6-digit SOC codes but are reported at 5-, 4- or 3-digit SOC codes, I average importance scores from the O*NET at lower digit level and attribute the average importance scores accordingly. SOC codes with less than 6 digits are around 15% of the dataset.

List of tasks

Manual tasks: arm-hand steadiness, manual dexterity, finger dexterity, control precision, multilimb coordination, response orientation, rate control, reaction time, wrist-finger speed, speed of limb movement, extent flexibility, dynamic flexibility, gross body coordination, gross body equilibrium, static strength, explosive strength, dynamic strength, trunk strength, stamina.

Cognitive tasks: category flexibility, fluency of ideas, originality, problem sensitivity, mathematical reasoning, number facility, deductive reasoning, inductive reasoning, information ordering, memorization, speed of closure, flexibility of closure.

Communication tasks: oral comprehension, oral expression, written comprehension, written expression.

3.B Additional tables

Table 3.B.1: Impact of exposure to Chinese import competition on the share of foreign workers without 1990

	OLS	2SLS
Column	(1)	(2)
Import penetration	0.0008***	0.0021***
	(0.0003)	(0.0007)
Individual level controls	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Commuting zone f. e.	Yes	Yes
Observations	1,336,772	1,336,772
R-squared	0.314	0.314
Kleibergen-Paap F		95
Mean foreign	0.17	0.17
Std. dev. import penetration	4.99	4.99

Notes - The dependent variable is a dummy equal to 1 for foreign workers. Foreign workers are defined as naturalized citizens and non-citizens. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.B.2: Impact of exposure to Chinese import competition on task intensity by nationality

	Foreigners			*Natives*		
	Manual	Cognitive	Communic.	Manual	Cognitive	Communic.
Column	(1)	(2)	(3)	(4)	(5)	(6)
			OLS estimates			
Import penetration	-0.0007	-0.0046	0.0025	-0.0259***	0.0002	0.0178***
	(0.0055)	(0.0073)	(0.0066)	(0.0055)	(0.0033)	(0.0045)
			2SLS estimates			
Import penetration	0.0074	-0.0156*	-0.0093	-0.0364***	0.0007	0.0248***
	(0.0060)	(0.0089)	(0.0087)	(0.0061)	(0.0041)	(0.0052)
Individual level controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Commuting zone f. e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	280,895	280,895	280,895	2,003,655	2,003,655	2,003,655
R-squared	0.872	0.842	0.809	0.868	0.797	0.783
Kleibergen-Paap F	363	363	363	171	171	171
Mean dep. variable	30.81	44.73	58.44	27.74	46.29	58.97
Std. dev. import penetration	6.71	6.71	6.71	5.36	5.36	5.36

Notes - Dependent variables are the average importance of manual, cognitive and communication tasks (detailed list in Appendix 3.A.3). Foreign workers are defined as naturalized citizens and non-citizens. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

Table 3.B.3: Impact of exposure to Chinese import competition on weekly wages by education and nationality

	Foreigners		*Natives*	
	Highly educ.	Low educ.	Highly educ.	Low educ.
Column	(1)	(2)	(3)	(4)
		OLS estimates		
Import penetration	0.0053***	0.0015	0.0038***	0.0008
	(0.0017)	(0.0014)	(0.0009)	(0.0009)
		2SLS estimates		
Import penetration	0.0032	0.0011	0.0039***	-0.0005
	(0.0025)	(0.0016)	(0.0011)	(0.0011)
Individual level controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Commuting zone f. e.	Yes	Yes	Yes	Yes
Observations	99,470	181,425	821,067	1,182,588
R-squared	0.418	0.237	0.390	0.271
Kleibergen-Paap F	126	757	241	121
Mean dep. variable	6.69	5.94	6.71	6.22
Std. dev. import penetration	6.99	6.54	5.70	5.06

Notes - The dependent variables are the logarithm of weekly wages. Foreign workers are defined as naturalized citizens and non-citizens. Highly educated workers are workers with at least some college education, while low educated workers are workers with high school diploma or less. Import penetration by commuting zone is the weighted sum of US imports from China across industries divided by the employment of the commuting zone as in Equation (3.1). The instrumental variable adopted is the import penetration of China into other high income countries computed as in Equation (3.3). The other high income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Individual level controls are gender, age, educational attainment, marital status, Siegel occupational prestige score and occupational categories. Regressions are weighted according to individual personal weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at state level.

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