Three Essays in Labor Economics

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Thesis submitted for the degree of
Doctor of Philosophy in Economics
Lugano, February 2024

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Acknowledgements

I am extremely grateful to my supervisor Fabrizio Mazzonna for his constant guidance and passionate support during my PhD. My professional growth over the last years owes everything to his insightful teachings and suggestions. I am also indebted to Raphaël Parchet and Giovanni Pica for their helpful comments during all the stages of my work and, in particular, for their careful guidance while working together on the second chapter of this thesis. I would like to thank Tito Boeri and Fabrizio Colella for taking part in my doctoral committee and for their valuable feedbacks that remarkably improved my work. I am sincerely grateful to all IdEP professors who have greatly contributed to my growth. A special thanks goes to all the colleagues who have shared with me this journey and from whom I have learned a lot. Last but not least, I am immensely thankful to my family and friends, whose presence and support have really made the difference.

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Introduction

This thesis investigates the impact of increased vulnerability to economic shocks in today's highly interconnected world, focusing in particular on their labor market effects. Leveraging the ideal research setting provided by Switzerland, it studies the role played by changes in migration and trade flows, but also the effectiveness of policy interventions implemented to face global shocks as the Covid-19 pandemic.

The first chapter focuses on the outbreak of the Covid-19 pandemic and evaluates the benefits of the lockdown implemented in Switzerland in spring 2020 to limit the spread of infections. Due to the disruptive effects of these measures on the functioning of labor markets (Cutler and Summers, 2020; Gros, 2020), assessing whether they were optimal requires a reliable evaluation of their actual benefits (Greenstone and Nigam, 2020). This work estimates the number of saved lives, proposing a novel age-structured SIRDC (Susceptible–Infected–Resolving–Deceased–reCovered) model that includes age-specific endogenous behavioral responses (Cochrane, 2020; Deforche, 2020). More in detail, this model predicts the daily amount of infections, hospitalizations, and deaths for different age groups in the absence of any policy intervention, assuming that individuals spontaneously respond to changes in the death rates of their age group and altruistically care about subjects belonging to other age groups (Long and Krause, 2017). Using individual-level data on the universe of Covid-19 cases, hospitalizations, and deaths, this SIRDC model predicts that the lockdown prevented more than 11,200 fatalities, including those due to the shortage of healthcare resources. These findings contribute to the policy debate on the effectiveness of non-pharmaceutical interventions, documenting their key role in reducing the number of infections and deaths caused by the pandemic, thus preventing far larger economic and social costs.

The second chapter investigates the impact of opening the labor market to qualified immigrants who hold fully equivalent diplomas as native citizens and share the same mother tongue. A growing literature documents the positive effects on native workers' wages and employment, especially when they can benefit from a high complementarity with incoming immigrants (Peri and Sparber, 2009; Ottaviano and Peri, 2012; D'Amuri and Peri, 2014; Foged and Peri, 2016; Beerli et al., 2021). However, when native and foreign workers share the same mother tongue and hold fully equivalent certifications, the adverse effects of increased competition may be borne by more substitutable native employees with less experience. This study contributes to a policy debate that has strengthened over the last decades, as policies that liberalize immigration have been at the center of the political agenda of several countries and have unleashed the fierce opposition of populist parties (Rodrik, 2020; Dorn and Zweimüller, 2021). Leveraging the 2002 opening of the Swiss labor market to qualified workers from the European Union through the recognition of their diplomas, the analysis focuses on Ticino, an Italian-speaking Swiss canton at the border with Italy. Using social security data and relying on a difference-in-differences strategy, there is evidence of a sizeable wage gain (5%) for high-ability middle-aged (30–49) Swiss workers in exposed economic sectors, while their younger (18–29) counterparts experienced a remarkable wage drop (7%) driven by the lower entry wages of newcomers in the labor market after the reform. These young workers also exhibited an increased likelihood of facing inactivity and out-migration. Such heterogeneity is explained by the close substitutability between immigrants and inexperienced natives sharing the same mother tongue and entering the labor market with comparable diplomas, while middle-aged incumbents take advantage of their knowledge of the local labor market (Borjas, 2003; Dustmann et al., 2017).

The third chapter investigates the role of exposure to adverse trade shocks as a driver of immigration flows and, in turn, the impact on workers' outcomes of simultaneous changes in both the volumes of trade activities and the nationality composition of the workforce. While a wide literature examines the labor market impact of either trade (Autor et al., 2013, 2014; Dauth et al., 2014; Acemoglu et al., 2016) or immigration shocks (Borjas, 2003; Peri and Sparber, 2009; Ottaviano and Peri, 2012; Gentili and Mazzonna, 2023), less is known on the effects driven by the interplay between them. Exchange rate shocks represent a unique case study to address this research question, since they affect trade flows and migration decisions (Keita, 2016; Nekoei, 2013). This chapter leverages the sharp Swiss Franc appreciation due to the unexpected repeal of the exchange rate floor with the Euro on January 15, 2015. First, using a difference-in-differences design, it shows that the increased import competition and lower export competitiveness that followed the shock led to an immediate rise in unemployment and drop in earnings for workers below age 30 and above age 50 in manufacturing industries, with spillover effects in service sectors. Second, it documents the impact of the shock on the employment of cross-border workers, who are sensitive to currency appreciations that imply an increase in the purchasing power of their earnings (Bello, 2020). Using a triple difference strategy that also compares border and non-border labor market areas, this work shows evidence of a far larger increase in the share of cross-border workers in industries characterized by higher trade exposure, with further detrimental effects on young resident workers' outcomes. This suggests that firms located close to the border may have limited the losses of trade competitiveness by reducing their costs through the employment of cross-border workers.

Overall, this thesis provides new empirical evidence that contributes to the economic and political debate on the labor market effects of shocks that are increasingly likely to affect today's globalized economy. These insights are meant to guide policymakers to develop effective measures that address their potential disruptive effects, discussing the actual benefits of some policies, the substantial heterogeneity of their effects, and mechanisms neglected so far.

Chapter 1

Saving lives during the Covid-19 pandemic: the benefits of the first Swiss lockdown

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1.1 Introduction

Since the end of 2019, all countries in the world have experienced a rapid spread of the Covid-19 epidemic, which has required the fast development of appropriate policy responses to face the increasing number of infections, hospitalizations and deaths. The majority of governments have therefore introduced different types of measures to reduce contacts among people. Such interventions have included bans on public events and gatherings of people, closures of national and regional borders, as well as school closures and the interruption of all non-essential business activities. These policies have been at the center of a heated debate, mainly due to their high economic and social costs.

A lockdown may have substantial negative effects on economic activities, leading to business disruption, job losses and earnings reductions. Recent surveys reveal that at least 42% of young people experienced a deterioration of their career prospects and serious income losses (ILO, 2020). Such detrimental consequences in terms of learning outcomes and disposable income are also reverberated in lower levels of wellbeing and worse mental health conditions (OECD, 2020b; Cutler and Summers, 2020).

The aim of this paper is to evaluate the number of lives which a lockdown can potentially save. Given the economic costs implied by this policy, a reliable estimate of its benefits is crucial to understand whether its adoption is actually optimal (Gros, 2020). In order to address our research question, we focus on the lockdown implemented in Switzerland in response to the first wave of Covid-19 infections. To the best of our knowledge, the existing literature has not provided yet an estimate of the lives saved by the Swiss lockdown in spring 2020.

Taking advantage of a unique dataset about the universe of individuals who tested positive for the disease, we estimate the number of potentially saved lives by developing a novel SIRDC model, which allows to predict the daily amount of infections, hospitalizations and deaths for different age groups in absence of lockdown. In particular, our model accounts for seasonal patterns characterizing the transmissibility of the virus (Atkeson, 2021) and includes age-specific endogenous behavioral responses (Cochrane, 2020). More specifically, we assume that not only individuals respond to changes in the death rate of their age group, but they are also *altruistic* and care about the well-being of other subjects. A basic SIR model, instead, would lead to overstate the impact of the policy right because it does not consider that citizens spontaneously reduce their contacts even in absence of government interventions. To obtain a reliable estimate of saved lives, we also take into account potential *overflow* deaths due to hospital overcrowding. This is particularly relevant if we consider that the impossibility of providing proper hospital treatments, especially in intensive care units (ICU), results in a higher mortality risk also for younger subjects.

Our SIRDC model suggests that the absence of any policy intervention in Switzerland would have resulted into approximately 11,500 deaths by September 1^{st}, plus 1,500 additional casualties due to the lack of available beds in intensive care units. Relying on a basic SIR model, instead, we would have predicted roughly 65,000 deaths, plus 62,000 fatalities due to the limited availability of healthcare resources. Such estimates would be in line with the simulations performed by the Imperial College Covid-19 Response Team. Neglecting hospital overcrowding, behavioral responses and seasonality, indeed, Flaxman et al. (2020) conclude that Switzerland would have reached 54,000 deaths by May 4^{th}. Our basic SIR model would deliver higher estimates only because we consider a time horizon which goes beyond May 4^{th} and reaches the end of May, when the contagion fades out.

Our work is related to a growing literature concerning the impact of restrictive measures which limit the spread of an epidemic, especially after the outbreak of Covid-19. For instance, Zhang et al. (2020) show that contacts among people were reduced by more than seven times in China thanks to physical distancing policies, while Fang et al. (2020) document that the lockdown in Wuhan reduced the number of potential infections by almost 65%. Some studies have also attempted an evaluation of the monetary benefits associated to the lives saved by the lockdown (e.g., Greenstone and Nigam, 2020; Thunström et al., 2020). However, these analyses often rely on simulations based on early limited data (Verity et al., 2020).

This work contributes to the current literature about the Covid-19 pandemic from both a methodological and an empirical point of view. First, we develop a novel age-structured SIRDC model that accounts for seasonal patterns and age-specific endogenous behavioral responses, including both an egoistic and an altruistic component. Second, we provide an estimate of the severity of Covid-19 based on rich data concerning the entire period of the first wave of infections in Switzerland. Third, to the best of our knowledge, this is the first estimate of the number of lives saved by the first Swiss lockdown in spring 2020.

The rest of the paper is organized as follows. Section 1.2 introduces the Swiss context and the policies implemented during the first wave of the Covid-19 pandemic, between March and the beginning of September. Section 1.3 describes the data. Section 1.4 presents our model and the estimates of the potential number of deaths in absence of containment measures. Section 1.5 focuses on overflow deaths due to hospital overcrowding. Section 1.6 concludes.

1.2 Background

After the outbreak of the Covid-19 epidemic in China and in several European countries, at the end of February 2020 Switzerland started facing the spread of the virus, with an increasing number of infections. As a consequence, massive public health non-pharmaceutical interventions became the only viable strategy to limit the contagion.

Switzerland is a Confederation made up of 26 independent and sovereign cantons, so interventions can be planned and implemented both at national and cantonal level. Indeed, some restrictive measures were already introduced, cancelling several public events, on February 26^{th} in the cantons at the border with Italy and France, where the first Covid-19 cases were reported.[1] Meanwhile, the first containment measure adopted at national level by the federal government on February 28^{th} was the banning of any event involving more than 1,000 participants.

However, because of the rapidly increasing number of infections throughout the country, the Swiss federal government intervened with more stringent measures. In

[1]The first official Covid-19 case in Switzerland was reported on February 25^{th} in Ticino, the most southern canton at the border with Italy.

particular, on March 17^{th} schools and non-essential economic activities were closed, while gatherings of more than five people were forbidden starting from March 20^{th}. Nevertheless, differently from other countries like Italy, Switzerland did not opt for a *strict* lockdown, with the general requirement to stay at home.

Although economic losses were expected to be severe also in a country with a high GDP per capita (World Bank, 2020) and *Human Development Index* score (United Nations, 2020), the Federal Council (2020) aimed at avoiding an unsustainable burden in terms of infections and lost lives. Such concern was particularly reasonable considering that the Swiss population has increasingly aged over the last decades and more than 20% of people are older than 65, hence far more likely to develop serious illnesses or eventually die from Covid-19. In light of the constrained availability of healthcare facilities, moreover, it was necessary to prevent a scenario in which access to life-saving treatments would have been denied to patients in need.

After reaching a peak during the first half of April, the number of infections and, consequently, deaths started to exhibit a decreasing pattern. As a result, lockdown measures were progressively loosened. On April 27^{th} several shops opened again, while schools restarted on May 11^{th} and the activities in the majority of offices and facilities could take place again from June 8^{th}.

1.3 Data

Our analysis is based on individual-level data released by the *Federal Office of Public Health* (FOPH) about the universe of individuals who tested positive for Covid-19 in Switzerland between February 24^{th} and May 15^{th}, during the first wave of the epidemic[2]. For each positive case in a specific Swiss canton on a certain day, this dataset contains information about age and gender, as well as the date of the onset of the first symptoms. Furthermore, these data also report whether and when an individual was hospitalized, specifying if intensive care was required and providing the exact days on which the patient entered and left the intensive care unit. Finally, we know whether and when the person eventually died. Table 1.1 summarizes these data.

In spite of relevant testing efforts, however, during the first wave of the pandemic asymptomatic cases were largely undetected. Because of the limited availability of resources, only people with severe symptoms were tested. This is the reason why we derive information about seroprevalence from the study conducted in Geneva by

[2]In addition, we exploit the number of deaths in each age group by the first week of September.

Table 1.1: Descriptive Statistics by Age Group (by May, 15^{th})

	Age Groups								
	0–9	10–19	20–29	30–39	40–49	50–64	65–79	80+	Total
Panel A: Positive Cases									
Number of Cases	153	862	3801	4106	4768	8318	4393	4059	30460
Share of Total Cases	0.50%	2.83%	12.48%	13.48%	15.65%	27.31%	14.42%	13.33%	100%
Share of Women	47.02%	58.58%	59.73%	57.20%	57.19%	50.29%	44.81%	60.70%	54.30%
Panel B: Hospitalizations and ICU									
Hospitalizations	26	33	110	136	258	866	1275	1187	3891
Hospitalizations/Cases	16.99%	3.83%	2.89%	3.31%	5.41%	10.41%	29.02%	29.24%	12.77%
ICU	1	1	5	15	27	132	239	78	498
ICU/Cases	0.65%	0.12%	0.13%	0.36%	0.57%	1.59%	5.44%	1.92%	1.63%
Average Days in ICU	-	-	-	4.33	10.50	16.25	11.41	8.66	11.30
Panel C: Deaths									
Number of Deaths	0	0	0	5	4	71	403	1112	1,595
Deaths/Cases	0.00%	0.00%	0.00%	0.12%	0.08%	0.85%	9.17%	27.39%	5.24%
Share of Women	0.00%	0.00%	0.00%	40.00%	25.00%	25.35%	31.27%	47.48%	42.32%

Notes: This table summarizes the individual-level data released by the Federal Office of Public Health, which cover the period between February 24^{th} and May 15^{th}, 2020. Panel A displays the number of officially reported positive cases, as well as the share of total cases in each age group and the share of women. Panel B shows the number of patients requiring hospitalization or intensive care in each age group, also expressed as a share of the total number of cases in the corresponding age group. In case of access to intensive care units, the data even report the exact dates of entry and exit, allowing to compute the average length of stay. Finally, Panel C displays the number of Covid-related deaths in each age group, indicating the corresponding case fatality rate and the share of total fatalities occurred among women.

Stringhini et al. (2020). In this way, it is possible to understand the extent to which younger subjects, who tend to be underrepresented in the official data, were actually affected by the spread of the disease.

These data are complemented by the yearly cantonal statistics provided by the *Federal Statistical Office* about the resident population and the weekly number of deaths by age. As we will discuss in Section 1.4, we also exploit the Value of Statistical Life (VSL) to model the age-specific individual behavioral responses. The average VSL for the Swiss population is derived from the estimates released by the Federal Office for Spatial Development (2019)[3]. To obtain an age-specific VSL[4], we rescale the estimates obtained by Murphy and Topel (2006) in the US by means of the Swiss average value.

As far as the healthcare supply in Switzerland is concerned, we rely on several sources. The *Organization for Economic Cooperation and Development* (OECD) provides indicators about the number of total and acute care hospital beds per 1,000 inhabitants, and the latest statistics available for Switzerland are for year 2018 (OECD, 2020a). We also refer to Rhodes et al. (2012), who estimated the number of intensive care beds in several European countries including Switzerland, expressing them as a percentage of total acute care beds. Besides, we rely on the information released by the *Swiss Society of Intensive Care Medicine* about the percentage of healthcare resources which could be exclusively allocated to Covid-19 patients. In order to derive the number of daily available beds, finally, we need statistics about the average length of stay in hospital and intensive care for Covid-19 patients. To this purpose, we exploit the FOPH dataset to compute the average number of days spent in ICU by these patients. In the case of individuals who were hospitalized but did not enter ICU, instead, FOPH data provide only the day of entrance, so we take advantage of the statistics available in Pellaud et al. (2020) about hospitalizations related to Covid-19 in Fribourg.

To estimate the number of overflow deaths due to hospital overcrowding, we finally need information about the mortality rates associated with being admitted to or rejected from hospital or ICU. While FOPH data allow to compute mortality rates for Covid-19 patients who received appropriate care, the corresponding estimates for rejected

[3]The most updated value refers to year 2017 and amounts to 6.7 million Swiss Francs. More information about the Swiss VSL is provided by Ecoplan (2016).

[4]The VSL should exhibit a hump-shaped relationship with age (Aldy and Viscusi, 2008). Indeed, the VSL not only reflects life expectancy, but also other age-dependent characteristics such as education and career prospects. Hence, after increasing with age, the VSL starts declining when the individual turns approximately 30.

individuals will be taken from the literature (Greenstone and Nigam, 2020; Rojas, 2020), since Switzerland never faced the problem of overcrowded hospitals during the first wave of the pandemic.

1.4 An estimate of potential *direct* deaths

The present section describes our estimates of the potential number of avoided *direct* deaths thanks to containment measures in Switzerland. The term *"direct"* refers to the fact that these estimates do not include the additional potential deaths due to hospital overcrowding, which will be computed in the next section.

We now proceed with the following steps. First, we focus on the initial phase of the epidemic, when the growth of infections was not influenced yet by any restriction, to determine the parameters which allow to predict the subsequent spread of the contagion in a counterfactual scenario without mitigation policies. Second, we develop a novel SIRDC model to estimate the potential number of infections and the corresponding deaths between March and the beginning of September. To this purpose, we use an age-specific *imputed* infection fatality rate derived from the data.[5]

However, before proceeding with our analysis, we need to address a preliminary issue, which requires an adjustment of the data. Indeed, older people, who are more likely to exhibit severe symptoms, tend to be over-represented among positive cases, while younger (and often asymptomatic) individuals are systematically under-reported. Therefore, the total number of predicted infections in the *counterfactual* scenario cannot be attributed to the different age groups on the basis of the shares retrieved from the original data.

To circumvent this issue, we exploit the results obtained by Stringhini et al. (2020) from the seroprevalence tests conducted in Geneva. They not only estimate the overall seroprevalence in the population in each of the five weeks between April 6^{th} and May 9^{th}, but they also compute how the relative risk varies depending on age. After computing the average value of seroprevalence over the five weeks, using the number of observations in each week as a weight, we exploit the specific relative risks to obtain the shares of people belonging to different age groups who have been actually infected in Geneva. At this point, for each age group we compute the ratio between the actual share of

[5] In order to check the robustness of our results, we also estimate the age-specific infection fatality rate of Covid-19 using an alternative approach based on a Bayesian model. See Appendix A.3 for more details.

infected people in Geneva and the corresponding share of infected individuals in our data. Such ratio represents an age group-specific factor k_a measuring the extent to which each age group in the canton of Geneva is underrepresented in the data (see Table 1.2). Since testing criteria in Switzerland are defined centrally by the FOPH, it is reasonable to assume that the factor k_a computed for Geneva can be applied to all the other cantons. Hence, after multiplying the number of reported cases in each age group by the corresponding adjustment factor k_a, the issue of over- or under-representation of different groups is overcome (Table 1.3).

Table 1.2: Adjustment Factors

Age	Estimated Seroprevalence	Adjustment Factor k_a
0–9	0.02808	44.908633
10–19	0.07546	30.858332
20–49	0.08774	7.7625095
50–64	0.06931	5.0841335
65+	0.04387	3.0066347

Notes: This table reports the values of seroprevalence in different age groups inferred from the results of Stringhini et al. (2020) and the coefficients which should be multiplied by the official number of reported positive cases to predict the actual number of infections.

1.4.1 Estimating R_0 during the early stage of the epidemic

As a first step, we estimate the *basic reproduction number* (R_0) of the disease, which reveals the number of individuals who are infected by a single positive person during the initial phase of the epidemic[6], when the population consists almost exclusively of susceptible individuals and the cumulative number of cases grows exponentially until some containment measures are introduced (Muggeo et al., 2020; Daddi and Giavalisco, 2020; Massad et al., 2005).

The starting date of the epidemic is identified as the first day when an incidence of at least 20 cases of Covid-19 per 100,000 people is registered after the adjustment described above. The duration of the initial phase, before the materialization of any effect due to containment measures, is computed by estimating when the linear growth

[6] If $R_0 = 1$, the number of infected people remains constant; if $R_0 < 1$, the number of infected people decreases; if $R_0 > 1$, the number of infected people increases.

Table 1.3: Descriptive Statistics by Age Group after adjusting the data (by May, 15^{th})

	Age Groups								
	0–9	10–19	20–29	30–39	40–49	50–64	65–79	80+	Total
Positive Cases									
Number of Cases	6871	26507	29366	31733	36911	42203	13181	12189	198961
Share of Total Cases	3.45%	13.32%	14.76%	15.95%	18.55%	21.21%	6.63%	6.13%	100%
Hospitalizations and ICU									
Hospitalizations	26	33	110	136	258	866	1275	1187	3891
Hospitalizations/Cases	0.38%	0.12%	0.37%	0.43%	0.70%	2.05%	9.67%	9.74%	1.96%
ICU	1	1	5	15	27	132	239	78	498
ICU/Cases	0.01%	0.00%	0.02%	0.05%	0.07%	0.31%	1.81%	0.64%	0.25%
Average Days in ICU	-	-	-	4.33	10.50	16.25	11.41	8.66	11.30
Deaths									
Number of Deaths	0	0	0	5	4	71	403	1112	1,595
Deaths/Cases	0.00%	0.00%	0.00%	0.02%	0.01%	0.17%	3.06%	9.12%	0.80%
Share of Women	0.00%	0.00%	0.00%	40.00%	25.00%	25.35%	31.27%	47.48%	42.32%

Notes: This table summarizes the dataset which combines the individual-level data released by the Federal Office of Public Health (February 25^{th} – May 15^{th}, 2020) and the seroprevalence results inferred from (Stringhini et al., 2020). Panel A displays the number of estimated positive cases, as well as the share of total cases attributed to each age group. Panel B shows the number of patients requiring hospitalization or intensive care in each age group, also expressed as a share of the total number of cases in the corresponding age group. In case of access to intensive care units, the data even report the exact dates of entry and exit, allowing to compute the average length of stay. Finally, Panel C displays the number of Covid-related deaths in each age group, indicating the corresponding *imputed* infection fatality rate and the share of total fatalities occurred among women.

of the *logarithm* of the cumulative number of infections changes slope. In practice, we estimate a *hockey stick* regression model that allows to identify the *breakpoint* date at which the slope of this linear relationship changes[7], as also displayed in Figure 1.1:

$$log\,(\mathbb{E}[Y_t]) = \beta_0 + \beta_1 t \tag{1.1}$$

where Y_t is the cumulative number of infections at day $t = 1, 2, ..., n$, after we have normalized the first day of the epidemic as day 1.

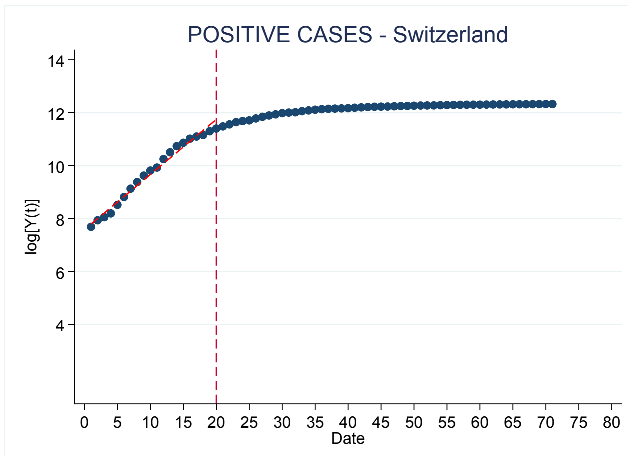


Figure 1.1: (Log) number of cumulative positive cases

Notes: This figure shows the evolution over time of the logarithm of the cumulative number of infections after March 5^{th}. The number of cases represented here is the one obtained after adjusting the official number of reported cases in light of the seroprevalence estimates by Stringhini et al. (2020). The change in the slope which occurs around the 20^{th} day reflects the end of an exponential growth of cases thanks to the implementation of restrictive measures in the country.

Table 1.4 reports the breakpoint dates estimated both for Switzerland and its seven macro-regions. Since the federal lockdown was announced on March 16^{th}, its effects are expected to be observed at most ten days later, considering that the incubation period for Covid-19 amounts to 5 days and other 4.5 days pass on average between the onset of the first symptoms and the test. This timing is exactly reflected in our estimates, with an anticipated effect in French cantons and in Ticino, where some restrictions were introduced earlier.

In light of these results, it is finally possible to compute the value of R_0 using the following equation (Massad et al., 2005; Daddi and Giavalisco, 2020):

[7] If the cumulative number of infections grows exponentially during the early stage of the epidemic, the *log* of the cumulative number of infections exhibits a linear growth over time.

$$Y_b = Y_1 * e^{(R_0-1)\gamma t} \tag{1.2}$$

Here, Y_b is the cumulative number of infections on the breakpoint date, Y_1 is the cumulative number of infections on the first day, while γ represents the *resolving* rate, so that $\frac{1}{\gamma}$ is the average infectious period during which an individual can transmit the virus to others. Such period can be expected to be similar to the incubation period and, indeed, according to Almeshal et al. (2020), it amounts to 5.8 days. Exploiting this value, we derive the estimates of R_0 reported in Table 1.4. Given that the basic reproduction number R_0 is defined as the product between the contact rate β and the average infectious period $1/\gamma$, we can finally retrieve the value of β.

Table 1.4: Estimates of R_0 during the early phase of the epidemic

Region	Starting Date	Breakpoint date	R_0	β
Lake Geneva	6^{th} March	23^{rd} March	2.2939	0.3955
Espace Mittelland	6^{th} March	26^{th} March	1.9005	0.3277
Northwestern Switzerland	5^{th} March	25^{th} March	1.9528	0.3367
Zurich	8^{th} March	24^{th} March	2.1808	0.3760
Eastern Switzerland	7^{th} March	24^{th} March	2.0553	0.3544
Central Switzerland	5^{th} March	25^{th} March	1.8601	0.3207
Ticino	3^{rd} March	22^{nd} March	2.1577	0.3720
Switzerland	5^{th} March	24^{th} March	2.0859	0.3596

Notes: This table reports the estimated length of the early phase of the epidemic - characterized by an exponential growth of cases - and the corresponding *basic reproduction number* R_0 in the main Swiss regions. The starting date is conventionally fixed when an incidence of at least 20 cases per 100'000 individuals is reached. The breakpoint date corresponds to a change in the growth rate of the cumulative number of cases due to containment measures (see Figure 1.1). The value of β is retrieved by multiplying R_0 and γ.

Table 1.4 reveals the existence of remarkable differences across Swiss regions in the intensity of the spread of the epidemic, which can also be explained by cultural heterogeneity (Mazzonna, 2020). A separate analysis of regions, however, would not allow to take into account the possibility that the contagion also spreads from one region to another, an aspect of key importance in a country where the degree of mobility is extremely high. Hence, in order to avoid underestimating the potential effects of lockdown measures, in the following sections of the paper we will rely on the number of infections, hospitalizations and deaths estimated at the national level.

1.4.2 Imputed infection fatality rates

The most widely used measure for the severity of a disease is the infection fatality rate (IFR), which indicates the proportion of deaths among all infected individuals, including those who are asymptomatic or undiagnosed. After adjusting the data in light of seroprevalence results, we can actually estimate the whole number of cases in each age group. Hence, by taking the ratio between the number of reported deaths and the number of cases within each age group, we obtain an age group-specific *imputed* infection fatality rate IFR_a for Covid-19[8]. These estimates will now be exploited to fit our model and derive the potential number of *direct* deaths in absence of restrictive measures.

1.4.3 Direct deaths in absence of restrictions

An age-structured SIRDC model with endogenous behaviors

The values of R_0 and β determined above can be now exploited to fit a model which allows to simulate the spread of the Covid-19 epidemic in Switzerland in absence of any mitigation policy. In particular, our aim is to improve the estimates which could be derived from a basic SIR model (see Appendix A.1) by considering a more realistic counterfactual scenario in which people tend to reduce spontaneously their contacts also in absence of any government intervention. Furthermore, following Atkeson (2021), we are also including in the model an additional component which accounts for seasonal variation in the spread of the virus. Indeed, as documented by the epidemiological literature (e.g., Park et al., 2020), the transmissibility of the virus changes during the year, reaching a peak towards the end of January.

As far as the time horizon of our predictions is concerned, we focus on the 180 days between March 5^{th} and September 1^{st}. Indeed, the present analysis is meant to estimate the benefits associated to the lockdown implemented in response to the first wave of infections. Moreover, such focus allows us to avoid a potential bias in our estimates arising from factors which changed after summer and led to the insurgence of the second wave of infections. However, Appendix A.4 also reports the results of our model when the time horizon is not restricted and we consider the entire period over which infections and deaths would occur.

[8]The value of IFR_a is null if no deaths are reported for age group a. The youngest individual who officially died from Covid-19 in Switzerland by May 15^{th} is aged 31.

We start from a simple SIRDC model (Fernández-Villaverde and Jones, 2022), in which individuals can be in one of five possible states: Susceptible (S), Infectious (I), Resolving (R), Dead (D) and reCovered (C). Since we are interested in estimating how the number of potential infections and deaths varies with age, we distinguish eight age groups[9].

Excluding vital dynamics (i.e., neglecting births and deaths that are unrelated to the epidemic, see Rowthorn and Maciejowski, 2020) and taking into account that the contagion may spread also across age groups, the model is described by the following system of five ordinary differential equations:

$$\frac{dS_a}{dt} = -\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a \tag{1.3}$$

$$\frac{dI_a}{dt} = \frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a - \gamma I_a \tag{1.4}$$

$$\frac{dR_a}{dt} = \gamma I_a - \theta R_a \tag{1.5}$$

$$\frac{dD_a}{dt} = \delta_a \theta R_a \tag{1.6}$$

$$\frac{dC_a}{dt} = (1 - \delta_a)\theta R_a \tag{1.7}$$

with a indicating one of the eight age groups, $a \in \{1, ..., 8\}$. N_a represents the total population belonging to a given age group, while N represents the total population, which does not vary over time since vital dynamics are here neglected.

The number of subjects in each compartment varies over time, but the stock across the five states remains constant:

$$\sum_{a=1}^{8} S_a(t) + \sum_{a=1}^{8} I_a(t) + \sum_{a=1}^{8} R_a(t) + \sum_{a=1}^{8} D_a(t) + \sum_{a=1}^{8} C_a(t) = \sum_{a=1}^{8} N_a(t) = N(t) = N$$

The rate at which susceptible individuals in each age cohort a become infectious is $-\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a = -\frac{\beta_0 IS}{N}$. Hence, it depends on the share of infections subjects in the total population, on the value of the contact rate β_0, which mirrors the speed of the

[9] To implement this model, we have followed Deforche (2020), but identifying eight different age groups rather than only two. See Appendix A.1 for more details.

transmission of the disease, and on the amount of individuals who are still susceptible. Infectiousness resolves at rate γ. Once individuals are no longer in the state in which they can infect others, they move to the resolving state. In each period t, then, a constant fraction of individuals (θ) in every considered age group leaves the resolving compartment, ending in one of the two final stages: either dead (with probability δ_a) or recovered (with probability $(1 - \delta_a)$)[10]. These last two states are permanent, that is, once in them, people can no longer change compartment We set $\beta_0 = 0.3596$ and $\gamma = 0.1724$, while δ_a indicates age-specific mortality rates[11]. Finally, we set $\theta = 0.1$. This value reflects the $\frac{1}{\theta} = 10$ days which on average an individual spends with the disease before it resolves.

The system of differential equations can be recursively estimated to predict the daily number of people in each compartment. Since the analysis is performed at national level, the initial conditions are represented by the individuals in each age group and compartment on March 5^{th} (see Appendix A.2). More in detail, the initial number of susceptible people in each age group is the number of individuals who had not been infected by March 5^{th}.

Since the infectious period $1/\gamma$ is assumed to be 5.8 days on average, the initial number of infectious individuals is represented by the number of new infections occurred during the 5.8 days before March 5^{th}[12]. The initial number of people in the resolving state is given by all the subjects who were infected previously[13]. Only one person aged 72 had officially died from Covid-19 before March 5^{th}, while no subjects had recovered yet on this date. Finally, dividing these values by the total population, we obtain the shares of individuals who initially belong to each age group and compartment[14].

At this point, following Cochrane (2020), we introduce in this framework an endogenous behavioral response common to all age groups. In other words, we suppose that when individuals start getting infected and dying, the contact rate β becomes lower, as people try to avoid the disease. Hence, we model the behavioral response as a function of the current death rate, according to the following equation:

[10]Note that this dynamics collapses to that of a basic SIR model if we aggregate R_a, D_a and C_a.

[11]Age-specific mortality rates are the imputed IFRs described in Section 1.4.2.

[12]The initial number of infectious individuals on March 5^{th} includes the infections registered between March 1^{st} and March 5^{th}, plus 80% of the infections occurred on February 29^{th}.

[13]Hence, individuals infected before February 28^{th}, plus 20% of those infected on February 29^{th}.

[14]The adjustment based on seroprevalence results described before is meant to obtain reliable values at this stage of the analysis, avoiding an over-representation of older individuals.

$$log(\beta_t) = log(\beta_0) - \alpha_D \frac{\Delta D_t}{N} \tag{1.8}$$

where $D_t = \sum_{a=1}^{8} D_{a,t}$ and $N = \sum_{a=1}^{8} N_a$.

We calibrate α_D as in Cochrane (2020). Using equation 1.8, we assign values to β_0, β_t, and ΔD_t to obtain the parameter α_D, which measures people's sensitivity to changes in the death rates. β_0 is the baseline contact rate ($\beta_0 = 0.3596$), while β_t is the lowest value of β which is observed. Thus, the calculations based on our data reveal that $\beta_t = 0.173$[15]. The peak in the variation of the daily number of deaths in Switzerland is 25 deaths, so $\Delta D_t = 25$. Finally, N is the total Swiss population in 2020. We recover $\alpha_D = 108697.16$.

However, we know that there is striking heterogeneity in mortality rates across age groups. If people's behavior is affected by their perceived personal risk, behavioral responses could greatly vary by age and imposing a common differential equation for β could be an unrealistic assumption. Thus, we adapt the behavioral differential equation to introduce age-specific responses. We model the behavioral response of each age group as a function of both the death rate for that particular age group and a fraction of the death rates registered for the other age groups (introducing both an *egoistic* and an *altruistic* component).

First of all, we assume that individuals care to the maximum possible level (= 1) to the death rate of people belonging to their own age group, so we keep a one-to-one relationship between $\frac{d\beta_a}{dt}$ and $\frac{dD_a}{dt}$.

Second, we assume that individuals are, at least partially, altruistic, and adjust their behavior also in response to changes in the death rates of other age groups. However, they weight other people's well-being less than their own, with an *altruism factor* equal to 0.27 (Long and Krause, 2017).

Third, we assume that people do not give the same importance to the death rates of all the other age cohorts, but rather they adopt a societal perspective. In other words, individuals give more weight to the death rates of those age groups that have a higher VSL. Therefore, if we consider the perspective of age cohorts $0-9$, $10-19$, $30-39$, $40-49$, $50-64$, $65-79$ and 80+, and we normalize their VSL by giving value 1 to the highest VSL (i.e., that of the age group $20-29$), we obtain the coefficients reported in column (1) of Table 1.5. When we adopt the perspective of individuals in group

[15] We recovered the lowest observed value for β from R_{0t}. Indeed, we first estimate the daily value for R_{0t}, and we recover the corresponding β_t from the relationship $R_{0t} = \frac{\beta_t}{\gamma}$

$20-29$, we have slightly different normalized coefficients, since, excluding the VSL of that group, the highest VSL becomes that of the cohort aged $30-39$. Normalizing it to 1, we obtain the coefficients displayed in column (2) of Table 1.5.

Table 1.5: Normalization coefficients by age group

Age	(1) Reference Group: 20-29	(2) Reference Group: 30-39
0 - 9	$0.9126 = \phi_{1,3}$	$0.9302 = \phi_{1,4}$
10 - 19	$0.9514 = \phi_{2,3}$	$0.9697 = \phi_{2,4}$
20 - 29	$1 = \phi_{3,3}$	-
30 - 39	$0.9810 = \phi_{4,3}$	$1 = \phi_{4,4}$
40 - 49	$0.8557 = \phi_{5,3}$	$0.8723 = \phi_{5,4}$
50 - 64	$0.5936 = \phi_{6,3}$	$0.6050 = \phi_{6,4}$
65 - 79	$0.2729 = \phi_{7,3}$	$0.2781 = \phi_{7,4}$
80 +	$0.0940 = \phi_{8,3}$	$0.0958 = \phi_{8,4}$

Notes: This table reports the normalized coefficients obtained by taking the ratio between the value of statistical life of each age group and the value of statistical life of a reference group. The reference categories are represented by the age groups 20–29 and 30–39, namely those characterized by, respectively, the first and second highest values of statistical life.

Following Atkeson (2021), we finally include in equation 1.8 a parameter $\psi(t)$ that captures seasonal patterns affecting the transmissibility of the virus:

$$\psi(t) = \omega * (cos((t+\tau) * 2\pi/365) - 1)/2 \tag{1.9}$$

where ω measures the amplitude of seasonal fluctuations and is set equal to 1, while τ identifies the peak in the transmission of the virus. In line with Atkeson (2021) and the epidemiological literature mentioned above (e.g., Park et al., 2020), we conventionally set this peak on January 31^{st}, thus $\tau = 33$[16].

Putting everything together, we now have age-specific differential equations for the behavioral responses which can be included in the age-structured SIRDC model:

[16] Indeed, 33 days pass between January 31^{st} and March 5^{th}.

$$\frac{dS_a}{dt} = -\frac{\beta_a \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a \tag{1.10}$$

$$\frac{dI_a}{dt} = \frac{\beta_a \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a - \gamma I_a \tag{1.11}$$

$$\frac{dR_a}{dt} = \gamma I_a - \theta R_a \tag{1.12}$$

$$\frac{dD_a}{dt} = \delta_a \theta R_a \tag{1.13}$$

$$\frac{dC_a}{dt} = (1 - \delta_a)\theta R_a \tag{1.14}$$

$$\frac{d\beta_a}{dt} = \frac{\beta_0}{exp\Big(\alpha_D\Big(\frac{dD_a}{dt} + 0.27\Big(\sum_{i=1, i\neq a}^{8} \phi_{i,3}\frac{dD_i}{dt}\Big)\Big) - \psi\Big)} - \beta_a$$

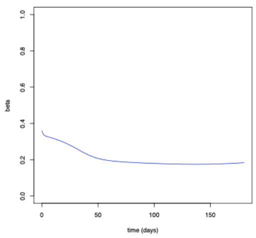
$$\text{for } a \in \{1,2,4,5,6,7,8\} \tag{1.15}$$

$$\frac{d\beta_a}{dt} = \frac{\beta_0}{exp\Big(\alpha_D\Big(\frac{dD_a}{dt} + 0.27\Big(\sum_{i=1, a\neq 3}^{8} \phi_{i,4}\frac{dD_i}{dt}\Big)\Big) - \psi\Big)} - \beta_a$$

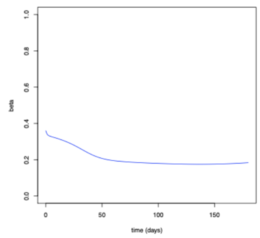
$$\text{for } a \in \{3\} \tag{1.16}$$

These equations imply an immediate reduction of contact rates for older individuals, while younger people tend to reduce their interactions more slowly since the death rate for their age group is low or even null. Figure 1.2 shows the evolution over time of the contact rates by age cohort.

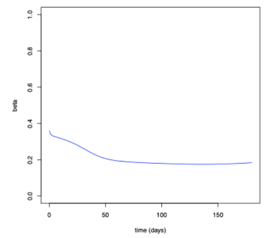
As before, N is normalized to 1, so that S_a, I_a, R_a, D_a, C_a represent the shares of population in each age group and compartment. As already mentioned, we consider a time horizon of 180 days. Therefore, instead of looking directly at the results for state D_a on September 1^{st}, direct deaths are obtained by applying the IFR to the cumulative number of infections predicted in each age group by that day. This allows to take into account the additional deaths which would have materialized in the first weeks of September. Figure 1.3 reports the evolution over time of the variables considered in our SIRDC model after aggregating the different age groups.



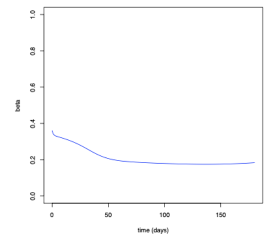
(a) Age $0-9$



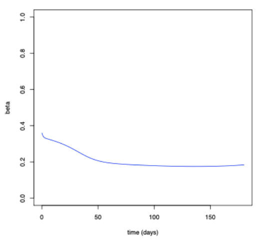
(b) Age $10-19$



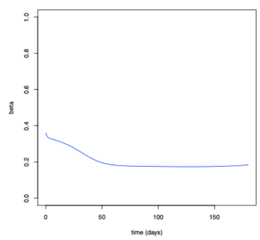
(c) Age $20-29$



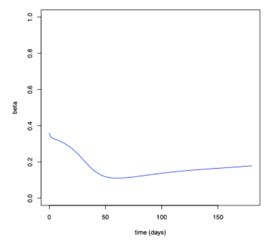
(d) Age $30-39$



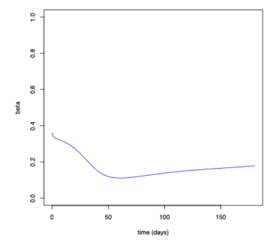
(e) Age $40-49$



(f) Age $50-64$



(g) Age $65-79$



(h) Age 80+

Figure 1.2: Contact rate by age group over time

Notes: This figure displays the evolution over time of the contact rates of individuals belonging to different age groups. Such dynamics reflect the differences in the intensity of the behavioral responses of these subjects. In particular, older individuals - namely those who are more likely to suffer from the most severe consequences of the disease - tend to reduce their contact rates more substantially in response to an increase in the number of deaths.

Results

Table 1.6 shows our estimates of the potential number of *direct* deaths[17] in absence of restrictive measures.

According to our SIRDC model which accounts for citizens' behavioral responses and for seasonal patterns, the spread of the virus in absence of any government intervention would have caused almost 11,500 deaths within six months from the beginning of the pandemic (see also Table A.4.1), especially among older age groups. Robustness evidence will be presented in Appendix A.3, where we discuss an alternative approach to derive the infection fatality rates.

[17]Note that IFR_a is null for the two of the three youngest age groups, as no deaths are reported in the official data. The youngest individual who has officially died because of Covid-19 in Switzerland is aged 31.

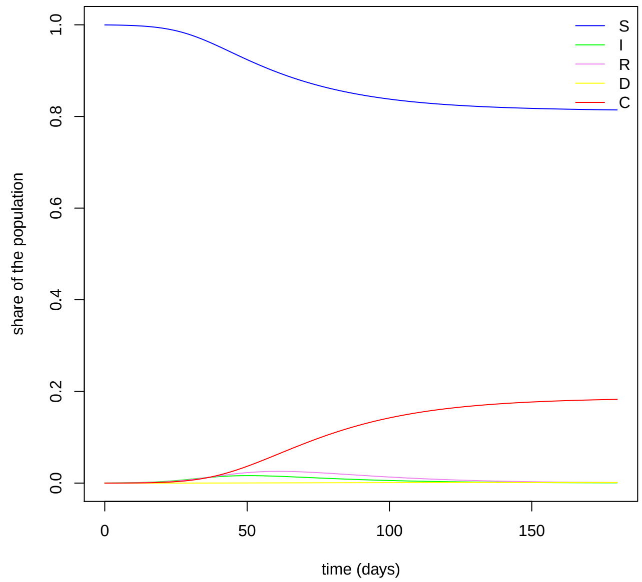


Figure 1.3: SIRDC model

Notes: This figure plots the evolution of the daily shares of individuals in each compartment according to the predictions of our SIRDC model over the time period considered.

1.5 An estimate of potential *overflow* deaths

The present section is dedicated to estimate the overflow deaths which would have occurred in a counterfactual scenario without lockdown measures. These fatalities would have resulted from hospitals reaching their capacity and being unable to serve some Covid-19 patients. In order to estimate them, we first need to quantify daily demand for specialized healthcare and daily supply of acute care and intensive care beds in Switzerland. Second, we need to assign mortality probabilities for cases requiring hospitalization or intensive care, when appropriate care is provided or denied.

1.5.1 Healthcare demand

The SIRDC model presented in Section 1.4.3 (as the basic SIR model in Appendix A.1) allows us to compute the daily number of new cases within each age group. On each day t, the share of new cases in age group a can be computed as $NC_{a,t} = (I_{a,t} - I_{a,t-1}) + (R_{a,t} - R_{a,t-1}) + (D_{a,t} - D_{a,t-1}) + (C_{a,t} - C_{a,t-1})$ in the SIRDC model. The actual number

Table 1.6: Direct deaths (infections until September, 1^{st})

		SIR Model			SIRDC Model		
Age	Pop	Cases	IFR_a	Deaths	Cases	IFR_a	Deaths
0–9	871,211	712,403	0.0000%	0	172,233	0.0000%	0
10–19	844,092	690,167	0.0000%	0	166,857	0.0000%	0
20–29	1,045,160	854,592	0.0000%	0	206,098	0.0000%	0
30–39	1,228,988	1,004,847	0.0158%	159	242,444	0.0158%	38
40–49	1,198,240	979,793	0.0108%	106	236,544	0.0108%	26
50–64	1,810,157	1,480,214	0.1682%	2,490	345,460	0.1682%	581
65–79	1,152,223	942,376	3.0574%	28,812	162,498	3.0574%	4,968
80+	453,828	371,150	9.1148%	33,830	64,411	9.1148%	5,871
	8,603,899	7,035,542		65,397	1,596,545		11,484

Notes: This table reports the number of direct deaths predicted according to both a basic SIR model and our SIRDC model accounting for seasonality and endogenous behavioral responses. For each model, the table displays the estimated number of infections in each age group and the corresponding number of direct fatalities, as well as the *imputed* infection fatality rate used for the computation.

of cases is then obtained multiplying $NC_{a,t}$ by the total Swiss population. In order to derive the demand for healthcare services by Covid-19 patients, we exploit our data to compute the share of infected individuals within each age group who were hospitalized or needed intensive care treatment[18].

1.5.2 Healthcare supply

As the survival probability of Covid-19 patients depends crucially on the provision of specialized care, we need precise information about the total number of available hospital and ICU beds In Switzerland. According to the OECD, in 2018 there were 3.6 acute care hospital beds per $1,000$ inhabitants in the country. Considering the population in 2020, the stock of curative hospital beds over the entire country turns out to be about $30,982$ beds. According to Rhodes et al. (2012), then, 3.1% of these acute care beds are for intensive care, giving us a stock of 960 beds in Switzerland. This figure is in line with the estimate provided by the Swiss Society of Intensive Care Medicine, which set the stock between 950 and 1000 beds in the 82 intensive care units

[18] We distinguish between people needing a hospital bed, but not intensive care, and people needing intensive care.

present on the Swiss territory. For the moment, we do not consider the possibility to improve health care supply, although there is some evidence that the total stock of ICU beds could be increased by 50% (icumonitoring.ch, 2020).

However, healthcare resources cannot be allocated only to Covid-19 patients and, indeed, before the spread of the virus, the daily average occupation rate of hospital and ICU beds was, respectively, 74% and 75% (Federal Statistical Office, 2020; European Society of Intensive Care Medicin, 2020). We assume that 50% of the stock of acute care beds can be allocated to the treatment of Covid-19 patients and, following the Swiss Society of Intensive Care Medicine, we fix the available stock of ICU beds for individuals affected by Covid-19 at 56%.

The daily availability of beds depends also on the length of stay in hospital and intensive care for the average patient. Hence, we exploit the data released by the FOPH to calculate the average number of days spent by a Covid-19 patient in ICU, obtaining an estimate of 11.3 days. Some of the individuals admitted to the ICU spend some time before in acute care beds, for an average of 1.9 days. We notice in the data that when the patients pass through the hospitalization phase before receiving intensive care, the date of the test assessing whether they have contracted the virus or not is subsequent to the hospitalization date. We can speculate that these 120 people are first admitted to the hospital and then moved to ICU once confirmed to be positive for Covid-19. With regard to patients who do not need ICU, instead, we cannot apply the same procedure described above to obtain the figure for hospitalizations, since we know when an individual enters the hospital, but the exit date is not available in the dataset. Therefore, we rely on Pellaud et al. (2020), who calculate several metrics in a retrospective cohort study about 196 hospitalized individuals with confirmed cases of Covid-19 in the Fribourg area. The average length of stay for Covid-19 patients who require hospitalization but not intensive care is 7 days.

Finally, daily supply is obtained dividing the stock of hospital and ICU beds which could be allocated to Covid-19 patients by the respective length of stay, obtaining an estimate of $0.5 * \frac{(30{,}982-960)}{7} = 2144.43$ daily hospital beds and $0.56 * \frac{960}{11.3} = 47.58$ daily places available in ICU.

1.5.3 Mortality rates

In order to estimate the number of *overflow* deaths, then, we need mortality rates for the cases in which people are admitted or not to the hospital or ICU. The individual data released by the FOPH also allow us to calculate the probability of death when patients receive appropriate care: indeed, the problem of overcrowding was never faced by Switzerland over the period covered by these data. In light of these data, the probability of dying for admitted patients is 17.9% in case of hospitalization and 52% in case of intensive care. These results are in line with those presented in international literature (Rojas, 2020; Greenstone and Nigam, 2020).

Since we cannot directly calculate the corresponding probabilities when the demand for healthcare cannot be accommodated, we follow Rojas (2020), who assumes that mortality increases threefold when a patient is rejected from a hospital (i.e., 53.7% in Switzerland). For ICU cases, we assume a survival probability of 10%, which is derived from the existing literature (Greenstone and Nigam, 2020; Ferguson et al., 2020). It is worth remarking that such assumptions imply that the mortality rates do not change depending on the age of the potential patient. This situation leads to a considerable number of overflow deaths also among younger people, explaining why these overflow deaths, compared to direct ones, are significantly higher in those categories. However, we do expect that reached a certain level of criticality, even younger people will face a significant risk of dying if left without proper healthcare interventions.

1.5.4 Overflow deaths

Exploiting the daily demand and supply of hospital beds computed above, we can now predict the daily number of deaths due to the shortage of healthcare resources. More in detail, on days when $demand \leq supply$, all people in need can receive appropriate care, and, therefore, survival probabilities are those estimated using FOPH data. When, instead, $demand > supply$ and facilities reach their capacity (Greenstone and Nigam, 2020), for the individuals who do not receive healthcare we apply the mortality probabilities of 53.7% and 90% for hospitalization and intensive care respectively.

Following the literature, we assume that age does not affect the probability of being rejected or admitted to healthcare facilities. In other words, the share of patients in each age group who do not receive appropriate care stays constant. For instance, if 20% of the cumulative number of patients cannot obtain a hospital bed on day t, that day 20% of patients belonging each age group are assumed not to have received the needed care. We obtain the total number of overflow deaths over the considered time period by summing up across all days. As reported in Table 1.7 (see also Table A.4.2), our SIRDC model allows to predict slightly more than 1,500 overflow deaths by September 1^{st}, all imputable to overcrowded ICUs. Such estimate is significantly lower in comparison to the one obtained by means of a basic SIR model. Endogenous individual responses and seasonal patterns, in fact, lead to a slower spread of the virus, flattening the number of new cases. As a result, since the fraction of new cases requiring hospitalization or intensive care remains constant, hospitals avoid reaching their maximum capacity.

Table 1.7: Overflow deaths (infections until September, 1^{st})

	SIR Model			**SIRDC Model**		
Age	Hospital	ICU	Total	Hospital	ICU	Total
0 - 9	772	256	1,028	0	19	19
10 - 19	140	57	197	0	4	4
20 - 29	799	194	993	0	14	14
30 - 39	967	669	1,636	0	49	49
40 - 49	1,549	889	2,438	0	66	66
50 - 64	2,856	4,743	7,599	0	336	336
65 - 79	16,083	17,888	33,971	0	858	858
80 +	10,729	3,680	14,409	0	178	178
	33,895	28,376	62,271	0	1,524	1,524

Notes: This table reports the number of deaths due to the shortage of healthcare facilities predicted according to both a basic SIR model and our SIRDC model accounting for seasonality and endogenous behavioral responses. For each model, the table displays separately the number of overflow deaths which can be attributed to the lack of hospital (but not ICU) beds and to the lack of ICU beds.

1.6 Conclusions

The introduction of lockdown measures to limit the spread of the Covid-19 pandemic has been at the center of a heated economic and political debate in the majority of countries. Several studies have therefore attempted an evaluation of the benefits associated to such restrictive measures. Focusing on the lockdown implemented in Switzerland in March 2020, our paper contributes to this extensive literature from both a methodological and an empirical perspective.

In order to estimate the number of potentially saved lives during the first wave of the pandemic in Switzerland, we have developed a new SIRDC model which predicts the evolution of the epidemic in absence of containment measures. In comparison to a basic model, our version includes additional features which make the counterfactual scenario more realistic. First of all, we incorporate age-specific endogenous behavioral responses. In other words, not only we consider that individuals would spontaneously reduce their contacts even in absence of a government intervention, but we also account for the fact that this response varies depending on age. Furthermore, by including a seasonality component, we avoid to neglect that the transmissibility of the virus is not constant over time and, after reaching a peak in winter, tends to become very low in summer.

Our predictions about the daily number of infections, hospitalizations and deaths are based on rich individual-level data concerning Covid-19 cases in Switzerland. In particular, we exploit these data to derive the initial conditions and the necessary parameters to fit our model. We also predict the number of additional casualties which would have occurred because of the constrained availability of healthcare facilities. Although Switzerland did not face serious issues of hospital overcrowding during the first wave of the pandemic, in fact, the absence of containment measures would have led to a higher number of deaths because of the lack of hospital beds, especially in intensive care units.

Table 1.8: Estimated Number of Saved Lives (by September, 1^{st})

		SIR Model			**SIRDC Model**		
	Actual	Direct	Overflow	Excess	Direct	Overflow	Excess
0–9	1	0	1,028	1,027	0	19	18
10–19	0	0	197	197	0	4	4
20–29	0	0	993	993	0	14	14
30–39	5	159	1,636	1,790	38	49	82
40–49	6	106	2,438	2,538	26	66	86
50–64	90	2,490	7,599	9,999	581	336	827
65–79	455	28,812	33,971	62,328	4,968	858	5,371
80+	1,215	33,830	14,409	47,024	5,871	178	4,834
	1,772	65,397	62,271	125,896	11,484	1,524	11,236

Notes: This table reports the number of saved lives in each age group according to both a basic SIR model and our SIRDC model accounting for seasonality and endogenous behavioral responses. The estimated number of saved lives is computed as the difference between the total number of predicted fatalities (direct and overflow) and the actual number of occurred deaths.

Although the features of our SIRDC model allow to improve the reliability of predictions, results should always be interpreted cautiously. Indeed, they depend on the assumptions concerning the structure of model, the value of its parameters and the utilization of health care resources.

According to our estimates, the absence of any policy intervention would have led to approximately 11,500 direct deaths within six months from the beginning of the pandemic, plus 1,500 overflow fatalities related to hospital overcrowding. Considering the actual number of Covid-19 related deaths over the same time period, our results suggest that more than 11,200 lives were saved by the lockdown, as reported in Table 1.8. This is a largely relevant result, especially if we consider the relatively short time period under analysis (until September 1^{st}), which also includes the summer months during which the spread of the disease decreases spontaneously.

Appendix A

A.1 An age-structured SIR model

The values of R_0 and β determined in Section 1.4.1 can be exploited to fit a *susceptible-infected-recovered* (SIR) model which allows to simulate the evolution of the spread of the epidemic in Switzerland if containment measures had not been implemented. Since we are interested in estimating the number of potential infections which would have occurred in each age group, we build an age-structured SIR model following Deforche (2020), but letting the age groups be eight (i.e., 0–9; 10–19; 20–29; 30–39; 40–49; 50–64; 65–79; 80+) rather than only two.

According to this model, which allows contacts between all age groups a, at any time each individual can be either Susceptible (S), Infectious (I) or Recovered (R). The last compartment not only includes those subjects who are not infectious any more, but also those who died because of the disease. Excluding vital dynamics (i.e., neglecting births and deaths that are unrelated to the epidemic, see Rowthorn and Maciejowski, 2020), the model is described by the following system of ordinary differential equations:

$$\frac{dS_a}{dt} = -\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a \tag{1.17}$$

$$\frac{dI_a}{dt} = \frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a - \gamma I_a \qquad \text{for } a \in \{1, ..., 8\} \tag{1.18}$$

$$\frac{dR_a}{dt} = \gamma I_a \tag{1.19}$$

The rate at which susceptible individuals in each age group a become infectious $\left(\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a\right)$ depends on the share of infectious subjects in the total population, on the value of the contact rate β_0, which mirrors the speed of the transmission of the disease, and on the remaining stock of susceptible individuals.

As previously mentioned, γ represents the rate at which infectiousness resolves: individuals who are no longer infectious move to the resolving state and cannot change compartment any more (Eksin et al., 2019; Toxvaerd, 2020). At each point in time, the cumulative stock of individuals across states remains constant: $\sum_{a=1}^{8}(S_a + I_a + R_a) = \sum_{a=1}^{8} N_a = N$, where N is the total population. Normalizing N to 1, S_a, I_a and R_a are interpreted as the shares of the population belonging to each compartment.

At this point, the system of differential equations can be recursively estimated to predict the daily number of people in each compartment after the beginning of the epidemic. Since the analysis is performed at national level, the initial conditions are represented by the individuals in each age group and compartment on March 5^{th}. We exploit the values of β_0 and γ discussed before ($\beta_0 = 0.3596$; $\gamma = 0.1724$).

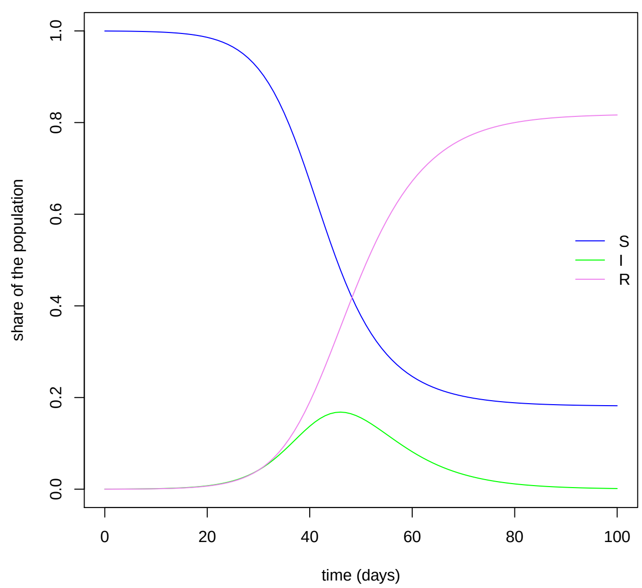


Figure A.1.1: SIR model

Notes: This figure plots the evolution of the daily shares of individuals in each compartment according to the predictions of a basic SIR model.

Figure A.1.1 plots the evolution over time of the predicted share of individuals who belong to each compartment when age groups are aggregated. It is interesting to observe that, when herd immunity is reached[19], the epidemic continues to spread

[19] Herd immunity is reached 46 days after March 5^{th}, i.e., on April 20^{th}.

at a slower rate, since each person infects less than one other person. Thanks to this model, therefore, we can estimate the total number of infected people by the end of the pandemic, who correspond to the amount of people in state R when the number of susceptible individuals does not decrease any more and nobody else contracts the disease[20]. At this point, having predicted the total number of infections in each age group, the corresponding number of potential deaths can be derived through the infection fatality rate computed from the data.

A.2 SIR and SIRDC Models - Initial Conditions

The initial values used to fit the SIR and SIRDC models are reported in Tables A.2.1 and A.2.2. The first subscript indicates the age group. These shares are calculated on March 5^{th}, 2020.

Table A.2.1: Initial values - SIR model

Susceptibles	**Infectious**	**Recovered**
$S_{1,0} = \frac{871031}{8603899}$	$I_{1,0} = \frac{90}{8603899}$	$R_{1,0} = \frac{90}{8603899}$
$S_{2,0} = \frac{843844}{8603899}$	$I_{2,0} = \frac{242}{8603899}$	$R_{2,0} = \frac{6}{8603899}$
$S_{3,0} = \frac{1044880}{8603899}$	$I_{3,0} = \frac{197}{8603899}$	$R_{3,0} = \frac{83}{8603899}$
$S_{4,0} = \frac{1228592}{8603899}$	$I_{4,0} = \frac{334}{8603899}$	$R_{4,0} = \frac{62}{8603899}$
$S_{5,0} = \frac{1197959}{8603899}$	$I_{5,0} = \frac{246}{8603899}$	$R_{5,0} = \frac{35}{8603899}$
$S_{6,0} = \frac{1809807}{8603899}$	$I_{6,0} = \frac{323}{8603899}$	$R_{6,0} = \frac{27}{8603899}$
$S_{7,0} = \frac{1152211}{8603899}$	$I_{7,0} = \frac{69}{8603899}$	$R_{7,0} = \frac{12}{8603899}$
$S_{8,0} = \frac{453792}{8603899}$	$I_{8,0} = \frac{36}{8603899}$	$R_{8,0} = \frac{0}{8603899}$

Notes: This table reports the shares of individuals in each compartment of the SIR model on March 5^{th}.

[20] Quite reassuringly, it is also possible to observe that the cumulated number of infections predicted by the model during the first days after March 5^{th}, when containment measures were not in place yet, are actually in line with those observed in the data.

Table A.2.2: Initial values - SIRDC model

Susceptibles	Infectious	Resolving	Dead	ReCovered
$S_{1,0} = \frac{871031}{8603899}$	$I_{1,0} = \frac{90}{8603899}$	$R_{1,0} = \frac{90}{8603899}$	$D_{1,0} = \frac{0}{8603899}$	$C_{1,0} = \frac{0}{8603899}$
$S_{2,0} = \frac{843844}{8603899}$	$I_{2,0} = \frac{242}{8603899}$	$R_{2,0} = \frac{6}{8603899}$	$D_{2,0} = \frac{0}{8603899}$	$C_{2,0} = \frac{0}{8603899}$
$S_{3,0} = \frac{1044880}{8603899}$	$I_{3,0} = \frac{197}{8603899}$	$R_{3,0} = \frac{83}{8603899}$	$D_{3,0} = \frac{0}{8603899}$	$C_{3,0} = \frac{0}{8603899}$
$S_{4,0} = \frac{1228592}{8603899}$	$I_{4,0} = \frac{334}{8603899}$	$R_{4,0} = \frac{62}{8603899}$	$D_{4,0} = \frac{0}{8603899}$	$C_{4,0} = \frac{0}{8603899}$
$S_{5,0} = \frac{1197959}{8603899}$	$I_{5,0} = \frac{246}{8603899}$	$R_{5,0} = \frac{35}{8603899}$	$D_{5,0} = \frac{0}{8603899}$	$C_{5,0} = \frac{0}{8603899}$
$S_{6,0} = \frac{1809807}{8603899}$	$I_{6,0} = \frac{323}{8603899}$	$R_{6,0} = \frac{27}{8603899}$	$D_{6,0} = \frac{0}{8603899}$	$C_{6,0} = \frac{0}{8603899}$
$S_{7,0} = \frac{1152211}{8603899}$	$I_{7,0} = \frac{69}{8603899}$	$R_{7,0} = \frac{11}{8603899}$	$D_{7,0} = \frac{1}{8603899}$	$C_{7,0} = \frac{0}{8603899}$
$S_{8,0} = \frac{453792}{8603899}$	$I_{8,0} = \frac{36}{8603899}$	$R_{8,0} = \frac{0}{8603899}$	$D_{8,0} = \frac{0}{8603899}$	$C_{8,0} = \frac{0}{8603899}$

Notes: This table reports the shares of individuals in each compartment of the SIRDC model on March 5^{th}.

A.3 An alternative estimate of the infection fatality rate

Considering that several approaches have been proposed so far in the literature to estimate the infection fatality rate of Covid-19, we now back up the imputed IFR discussed in Section 1.4.2 by estimating the severity of the disease with an alternative methodology. More specifically, we follow the approach proposed by Rinaldi and Paradisi (2020), which relies on the use of administrative data concerning death counts and demographic information.

A potential concern regarding the *imputed* IFR reported in Table 1.6, indeed, is represented by the fact that official data about Covid-19 cases may misrepresent the actual number of deaths related to the spread of the virus. FOPH deaths data may present a downward bias because people might die at home (because of Covid-19) or in other non-medical facilities, and remain untested. This situation can be present if individuals decide not to go to the hospital, or they are not in a position to go. At the same time, official Covid-19 deaths data can present an upward bias since a fractions of those who died because of the pandemic where already severely-ill individuals, who might have died over the following few weeks or months without the virus. Thus, Covid-19 has simply slightly anticipated their death.

In the attempt to correct for these biases, we use weekly administrative data about the deaths recorded between 2000 and 2020[21] by the Federal Statistical Office, which

[21] Data provide information about gender, age-group (5 years bin) and cantonal residence.

also provides demographic information at cantonal level[22]. We then elaborate these data to identify eight age groups (0–9; 10–19; 20–29; 30–39; 40–49; 50-64; 65–79; 80+) in the seven major Swiss regions (Lake Geneva, Espace Mittelland, North-West Switzerland, Zurich Region, Eastern Switzerland, Central Switzerland and Ticino).

Exploiting such information, we build a Bayesian model which fits age-stratified mortality and demographic data for the seven regions between 2000 and 2020 over the weeks 11-19, namely those characterized by the Covid-19 outbreak. Specifically, starting from a simple standard binomial mortality mode, we assume that deaths are binomially distributed and in weeks affected by Covid-19 the baseline lethality rate is augmented by a factor that indicates the interaction between the IFR and the infection rate of Covid-19. Further, we assume that mortality is not correlated between different age groups. The model is described with the following binomial equations:

$$D_{i,a,y} \sim \text{ Binomial}(\delta_a,\ N_{i,a,y}) \text{ for } y \in \{2000, ..., 2019\} \tag{1.20}$$

$$D_{i,a,2020} \sim \text{ Binomial}(\delta_a + \delta_a^{Covid} * \theta_i,\ N_{i,a,2020}) \tag{1.21}$$

where i denotes the macro-region, y the year, and a one of the eight age groups $(0-9; 10-19; 20-29; 30-39; 40-49; 50-64; 65-79; 80+)$. $D_{i,a,y}$ and $N_{i,a,y}$ are, respectively, the total deaths and population in macro-region i, year y, and age range a.

The baseline lethality rates δ_a are assumed to be constant across macro-regions and years, but can vary across age groups. Before 2020, the infection fatality rates δ_a^{Covid} are assumed to be equal to zero, while in 2020, they are heterogenous across age ranges and fixed in the other dimensions. Finally, the infection rates θ_i are region-specific but constant across age groups.

The identifying assumption is that in the absence of the Covid-19 outbreak, the weekly deaths recorded in 2020 would have been the same on average as the ones in the previous twenty years. We provide visual evidence (Figure A.3.1) about the extent to which this assumption is satisfied. Indeed, over the first 10 weeks of 2020, excess mortality (calculated as the number of deaths in 2020 versus the average value of deaths over the years between 2000 - 2019) is substantially null. However, we can not check whether the composition of the typologies of deaths changes over time and particularly in 2020, given that statistics on the causes of deaths are not available.

[22]Data provide information on the total population, by gender and age.

Using Markov Chain Monte Carlo procedures, we estimate an overall Infection Fatality Rate for Covid-19 of 1.087123% (95% confidence interval 0.2899833% − 2.038417%), with striking heterogeneity across age groups (see Table A.3.1).

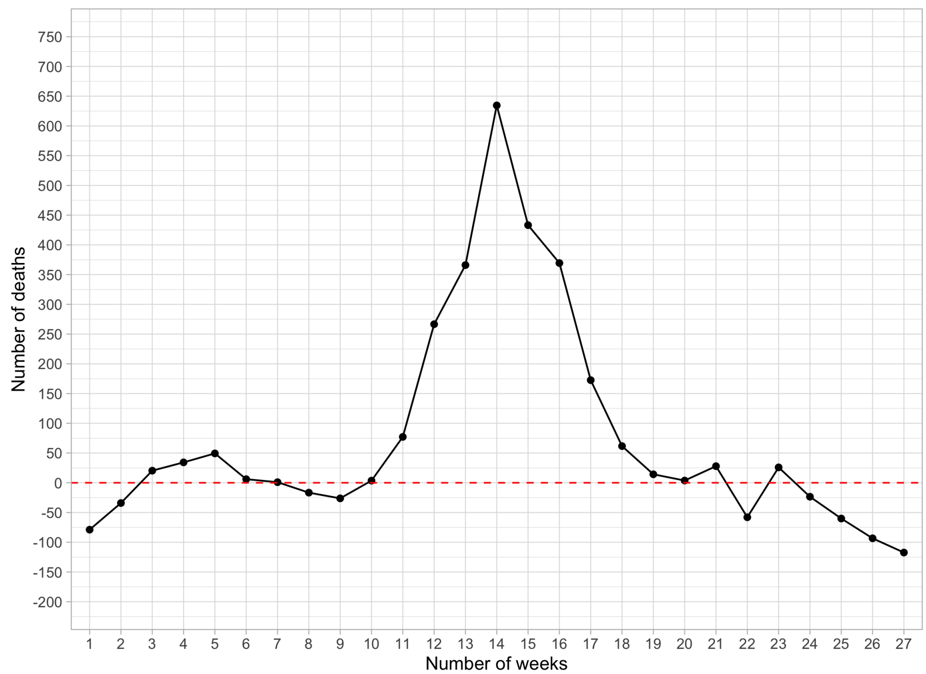


Figure A.3.1: Excess mortality 2020 vs. mean 2000-2019

Notes: This figure plots the weekly difference between the deaths counts in 2020 and the corresponding mean computed over the years between 2000 and 2019. During the first ten weeks of 2020, excess mortality is approximately zero in expectation, while during the phase of the pandemic outbreak (weeks 11-19) excess mortality becomes significantly positive.

As required with a Bayesian model, we specify priors for all the parameters we are interested in monitoring, i.e., $\delta_a, \delta_a^{Covid}, \theta_i$. We choose uninformative priors for all parameters:

$$\delta_a \sim \text{Uniform}[0,\ 0.1] \tag{1.22}$$
$$\delta_a^{Covid} \sim \text{Uniform}[0,\ 0.3] \tag{1.23}$$
$$\theta_i \sim \text{Uniform}[0,\ 0.2] \tag{1.24}$$

To derive point estimates and respective 95% confidence intervals for the parameters of interest, we employ a Markov Chain Monte Carlo procedure, that allows us to

Table A.3.1: Infection fatality rates by age group

Age groups	Median	Confidence interval
0 - 9	0.00016	(0.0000056 - 0.00110)
10 - 19	0.00023	(0.0000089 - 0.00130)
20 - 29	0.00014	(0.0000045 - 0.00094)
30 - 39	0.00019	(0.0000064 - 0.00120)
40 - 49	0.00023	(0.0000078 - 0.00150)
50 - 64	0.00023	(0.0000076 - 0.00160)
65 - 79	0.01300	(0.0031 - 0.03000)
80 +	0.17000	(0.047 - 0.29000)

Notes: This table reports the age group-specific infection fatality rates computed by means of the Bayesian approach, as well as the corresponding confidence intervals.

calculate the median and the confidence intervals of the posterior distributions of δ_a, δ_a^{Covid}, and θ_i, using as model equations (6) and (7) [23]. We draw 100,000 samples from the joint posterior distribution and use 50 independent chains. The burn in interval is fixed at 20000, and the thinning interval is 30. Convergence is checked (and satisfied) visually with Gelman-Rubin diagnostic. Our estimates are robust to the definitions of alternative distributions of the priors.

Table A.3.2 shows our estimates of the potential number of *direct* deaths in absence of restrictive measures (both for SIR and SIRDC models), when we use the infection fatality rates estimated through this Bayesian approach. As previously mentioned, this approach leads to higher infection fatality rates, which result in more potential *direct* deaths, also among younger age groups.

It is worth underlining here that such differences in the infection fatality rates are also reverberated in the slight discrepancies between the number of cases predicted by the SIRDC model reported in Tables 1.6 and A.3.2. According to our SIRDC model, indeed, individual behavioral responses depend on the number of daily deaths. Hence, changes in the fatality rate imply differences in the intensity of reduction of the contact rate β_a and in the number of predicted infections.

Since an alternative infection fatality rate leads to a different number of predicted infections, in Table A.3.3 we report the corresponding overflow deaths due to the lack of available beds in intensive care units.

[23] The likelihood function is composed of 5 equations for each combination macro-region - age group, for a total of $21 * 7 * 8 = 1176$ equations

Table A.3.2: Direct deaths (infections until September, 1^{st})

		SIR Model			SIRDC Model		
Age	Pop	Cases	IFR_a	Deaths	Cases	IFR_a	Deaths
0–9	871,211	712,403	0.016%	114	159,980	0.016%	26
10–19	844,092	690,167	0.023%	159	154,907	0.023%	36
20–29	1,045,160	854,592	0.014%	120	191,341	0.014%	27
30–39	1,228,988	1,004,847	0.019%	191	225,456	0.019%	43
40–49	1,198,240	979,793	0.023%	225	219,719	0.023%	51
50–64	1,810,157	1,480,214	0.023%	340	331,345	0.023%	76
65–79	1,152,223	942,376	1.300%	12,251	181,062	1.300%	2,354
80+	453,828	371,150	17.00%	63,095	51,367	17.00%	8,732
	8,603,899	7,035,542		76,495	1,515,177		11,345

Notes: This table reports the number of direct deaths predicted according to both a basic SIR model and our SIRDC model accounting for seasonality and endogenous behavioral responses. For each model, the table displays the estimated number of infections in each age group and the corresponding number of direct fatalities, as well as the *Bayesian* infection fatality rate used for the computation.

Table A.3.3: Overflow deaths (infections until September, 1^{st})

	SIR Model			SIRDC Model		
Age	Hospital	ICU	Total	Hospital	ICU	Total
0 - 9	772	256	1,028	0	18	18
10 - 19	140	57	197	0	4	4
20 - 29	799	194	993	0	14	14
30 - 39	967	669	1,636	0	47	47
40 - 49	1,549	889	2,438	0	63	63
50 - 64	2,856	4,743	7,599	0	333	333
65 - 79	16,083	17,888	33,971	0	1,032	1,032
80 +	10,729	3,680	14,409	0	138	138
	33,895	28,376	62,271	0	1,649	1,649

Notes: This table reports the number of overflow deaths due to the shortage of healthcare facilities predicted according to both a basic SIR model and our SIRDC model accounting for seasonality and endogenous behavioral responses. For each model, the table displays separately the number of overflow deaths which can be attributed to the lack of, respectively, hospital (but not ICU) and ICU beds.

A.4 Results from the SIRDC model without restrictions on the time horizon

This Appendix reports the estimates derived from our SIRDC model accounting for seasonality and endogenous behavioral responses when we consider the entire time horizon until the contagion finally fades out and we do not restrict our attention only on the first six months after the beginning of the pandemic, before the outbreak of the second wave of infections.

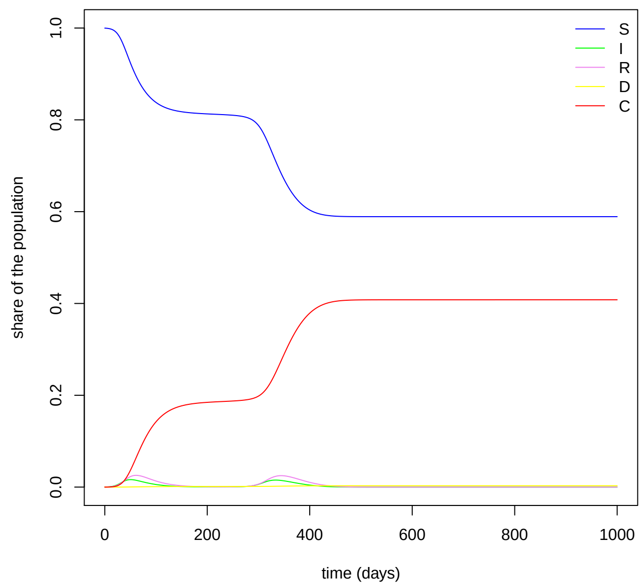


Figure A.4.1: SIRDC model - Time horizon: 1000 days

Notes: This figure plots the evolution of the daily shares of individuals in each compartment according to the predictions of our SIRDC model in absence of restrictions on the time horizon.

Figure A.4.1 shows that the model predicts also a second peak of infections after 200 days. The dynamics stabilizes after approximately 500 days, when 40% of Swiss individuals have been infected.

Tables A.4.1 and A.4.2 report the corresponding number of direct and overflow deaths by age group. In absence of restrictions on the time horizon, our model would predict roughly 28,500 fatalities, more than twice the value over the first six months (see Tables 1.6 and 1.7).

Table A.4.1: Direct deaths - SIRDC model

Age	Cases	IFR_a	Deaths
0–9	381,119	0.0000%	0
10–19	369,223	0.0000%	0
20–29	456,055	0.0000%	0
30–39	536,458	0.0158%	85
40–49	523,409	0.0108%	57
50–64	764,014	0.1682%	1,285
65–79	360,673	3.0574%	11,027
80+	142,946	9.1148%	13,029
	3,533,897		25,483

Notes: This table reports the total number of direct deaths predicted by our SIRDC model accounting for seasonality and behavioral responses. The table displays the estimated number of infections in each age group and the corresponding number of direct fatalities, as well as the *imputed* infection fatality rate used for the computation.

Table A.4.2: Overflow deaths - SIRDC model

Age	Hospital	ICU	Total
0 - 9	0	40	40
10 - 19	0	9	9
20 - 29	0	30	30
30 - 39	0	104	104
40 - 49	0	138	138
50 - 64	0	703	703
65 - 79	0	1,775	1,775
80 +	0	368	368
	0	3,167	3,167

Notes: This table reports the total number of overflow deaths due to the shortage of healthcare facilities predicted by our SIRDC model accounting for seasonality and behavioral responses. The table displays separately the number of deaths which can be attributed to the lack of, respectively, hospital (but not ICU) and ICU beds.

Chapter 2

Opening the Labor Market to Qualified Immigrants: A Double-Edged Sword for Native Employees

with F. Mazzonna, R. Parchet and G. Pica (Università della Svizzera italiana)

2.1 Introduction

The economic and political debate on the opening of labor markets to immigrant workers has involved the majority of countries over the last decades. On the one side, qualified immigrants play a crucial role for emerging countries aiming at raising the level of human capital of the workforce, as well as for advanced economies that are increasingly relying on foreign workers to deal with population ageing and skills shortages (see Peri, 2016, for a review). On the other side, the fear of harmful consequences for native workers has led to a growing support for right-wing populist parties that contest migration and, more generally, globalization (Rodrik, 2020).

A large literature in economics has shown evidence of positive effects on native workers' wages and employment when immigrants are either unskilled (Foged and Peri, 2016), experience linguistic barriers (Peri and Sparber, 2009), or have skills complementary to those of (high-skilled) native workers (Beerli et al., 2021). These complementarities lead to higher total factor productivity and wages (Borjas, 1999; Peri, 2012; D'Amuri and Peri, 2014), with natives who exploit their comparative advantage by taking communication-intensive and better paid managerial positions (Peri and Sparber, 2009; Manacorda et al., 2012; Ottaviano and Peri, 2012; Basten and Siegenthaler, 2019). Yet, opening the labor market to qualified immigrants could be a double-edged sword for native employees, especially when foreign workers speak the same mother tongue and hold fully equivalent certifications with respect to natives, with potentially harmful effects for the most substitutable native workers, namely, the young and those who lack experience in the local labor market.

This paper studies the heterogeneous effects of the 2002 Agreement on the Free Movement of Persons (AFMP) between Switzerland and the European Union on the labor market outcomes of qualified native workers with a different degree of attachment to the local labor market. This agreement has implied the recognition of diplomas and professional qualifications of workers from EU countries, granting them access to the Swiss labor market without the need to acquire further certifications.

We focus on Ticino, an Italian-speaking Swiss canton where Italian workers represent on average 42% of private sector employees. This is a very large share if compared to the fraction of non-Swiss employees in the whole country, which over our sample period amounts on average to 25% of the total workforce.

For identification, we rely on a difference-in-differences approach that compares the evolution of the real wages and employment status of native employees in sectors with a high intensity of occupations exposed to the recognition of EU certifications to the evolution of the same outcomes of native employees in less exposed sectors, before and after the policy change. In the Swiss setting, qualifications may be required also for lower-skilled jobs in some specific sectors. Thus, qualified workers affected by the reform are not necessarily those employed in high-skilled occupations.

We document three main effects of the AFMP. First, while the fraction of Italian employees grew in all sectors after the introduction of the AFMP, we estimate a further increase of more than 3 percentage points in treated sectors. This increase is mainly driven by young immigrants and corresponds to approximately 23% of the pre-policy share for this age group.

Second, the increased competition on qualified native workers from qualified immigrants had a large and statistically significant negative impact (-7%) on the real wages of young (18–29) Swiss employees; an impact that turns positive for middle-aged (30–49) native employees (+5%), and fades away for older employees (50–64). The wage gains experienced by middle-aged incumbent employees accrue mostly to high-ability workers and are more likely to materialize when negotiating a new working contract with a different firm. The negative effect on the youngest age group is explained by the lower entry wages of young natives who enter the labor market after the policy change, while the wages of young incumbents even increased. More in detail, the steep reduction in new entrants' wages reflects not only the direct effect of increased competition from immigrant workers on wages, but also the indirect effect through changes in the composition of the labor force. Indeed, we observe that, after the reform, the age (and likely the education level) at which young natives enter the labor market in treated sectors decreases from 23 to 22. We speculate that this drop may be due to the concurrent increase in the share of slightly older resident citizens aged 25–29 (likely with a college degree) moving to other cantons instead of entering the local labor market. This age-driven composition effect explains at least 8.5% of the wage drop estimated for the workers in this age range.

Third, we find that young native residents, especially those entering the labor market for the first time after the liberalization of qualified immigration from the EU, were more likely to become inactive (i.e., to leave the labor force) or to leave the region. Conversely, we document a decrease in the probability of leaving the labor force for older Swiss employees, a result consistent with existing evidence showing that a higher income reduces the probability of early retirement (Kuhn et al., 2021).

The observed heterogeneity across age groups in the effect of the liberalization of qualified immigration on natives' wages and employment status is likely due to the fact that, in the absence of linguistic barriers, young qualified immigrants are close substitutes of young natives entering the labor market with comparable diplomas and no experience; at the same time, they are complementary to middle-age experienced native workers with a deeper knowledge of the local labor market (Borjas, 2003; Ottaviano and Peri, 2012). We strengthen this interpretation showing that the real wages of incumbent, thus experienced, Italian employees have not been harmed by the inflow of new Italian workers.

We complement our findings with a descriptive analysis of the evolution of the labor market at the aggregate (regional) level. We show that after the introduction of the AFMP (*i*) the labor market in Ticino experienced a sharp expansion, mainly driven by the growing number of young and middle-aged Italian employees; (*ii*) the wages of Swiss workers in the youngest age group suffered a steeper decline (as compared to the already declining pre-policy trend); (*iii*) the wages of middle-aged Swiss workers went up; (*iv*) the share of inactive young native citizens increased; finally, (*v*) transitions to inactivity of older Swiss employees became less frequent.

Our paper contributes to the large literature investigating the impact of immigration on natives' labor market outcomes by focusing on a setting characterized by an inflow of same-language foreign qualified workers. Language barriers have been shown to be an important factor preventing migrants to substitute natives (see, e.g., Ottaviano and Peri, 2012). We find that experienced (i.e. middle-aged and older) natives are shielded from the detrimental effects of qualified migration, even in a context in which natives can be more easily replaced by migrants because they speak the same mother tongue. The burden of increased competition from qualified immigrants is instead borne by young (inexperienced) natives.

Our paper is closely related to the existing studies on the opening of the Swiss labor market to immigrants from EU countries. Focusing on cross-border workers, Beerli et al. (2021) show that the AFMP allowed firms in knowledge-intensive sectors, especially in the field of high-tech manufacturing, to acquire new skills that were previously scarce. The resulting productivity growth led to an increase in the number of firms and to wage gains for highly educated natives in top managerial positions (Basten and Siegenthaler, 2019). Consistent with this evidence, Cristelli and Lissoni (2020) find that the AFMP fostered innovation and the development of new patents in Switzerland thanks to the inflow of cross-border inventors who turned out to be highly complementary to Swiss incumbents. Related to this, Dicarlo (2022) shows evidence of a brain drain effect of the AFMP on the Italian side of the border, with an increase in firms' exit and a reduction of surviving firms' productivity, which in turn led to lower wages for their employees.

We complement these findings by showing that the effect is heterogeneous even among skilled natives and depends crucially on workers' experience.[1] We find that the gains are concentrated among middle-aged experienced incumbents, while young new entrants face wage losses and an increasing probability of becoming inactive. Similar findings are reported by Dustmann et al. (2017), who analyze the inflow of low-skilled Czech workers in Germany after the fall of the Berlin Wall. Although their setting is different from ours, they show that the adverse effects of increased competition were borne by individuals entering the labor market after the shock, who protected *insiders* from unemployment and wage losses. Dustmann et al. (2013) also discuss how immigration negatively affects individuals at the bottom of the wage distribution, who are likely younger. Conversely, a positive effect of high-skilled immigration, which enhances technological progress, materializes at the top of natives' wage distribution (Dustmann et al., 2009).

[1] Our identification strategy differs from Beerli et al. (2021) who rely on firms' distance from the border. We use instead the differential exposure of economic sectors to the recognition of EU qualifications. Such an alternative identification strategy arguably does not suffer from the potential endogeneity of firms' location choices.

Our study is also related to the existing research that investigates the impact of policies that liberalize the labor market by recognizing immigrants' occupational qualifications. For instance, Brücker et al. (2021) document that immigrants with recognized diplomas in Germany can access regulated occupations that offer better employment opportunities and higher wages with respect to those of other foreign workers. Regarding the impact of such policies on native workers' outcomes, Prantl and Spitz-Oener (2020) examine the impact of the massive inflow of East Germans in West Germany after the fall of the Berlin Wall, differentiating between sectors with different levels of regulation strictness. In a setting close to ours, with absence of linguistic barriers and immigrants holding occupation-specific degrees equivalent to those of natives, they find that West Germans' wages declined in highly competitive sectors and remained unaffected in sectors where a high degree of regulation limited the entry of new firms and increased incumbents' bargaining power.

Another branch of the existing literature on immigration deals with the role of natives' bargaining power when negotiating new contracts, arguing that wage gains arise from better outside options and, in particular, from a deeper knowledge of the local labor market (Moreno-Galbis and Tritah, 2016). In this framework, the inflow of qualified immigrants with lower reservation wages leads to positive externalities for experienced native individuals (Battisti et al., 2018), who obtain better-paid job positions. On the contrary, young individuals at the beginning of their careers – who do not have any experience-led informational advantage – are more exposed to competition. For instance, Aepli and Kuhn (2021) show that Swiss employers close to the frontier substitute young resident apprentices in need to be trained with less expensive and already qualified cross-border workers. Accordingly, Bächli and Tsankova (2023) investigate the effects of the AFMP on native citizens' educational choices and show that the growing presence of cross-border workers active in STEM occupations induced young Swiss individuals to enroll in vocational universities to acquire non-STEM skills complementary to those of incoming immigrants.

The policy relevance of our research lies in its contribution to the extensive debate on the consequences of opening the labor market to qualified immigrants. Policies aiming at removing barriers for foreign workers have been at the center of the political agenda of several countries and have unleashed the fierce opposition of some parties (Dorn and Zweimüller, 2021).

The rest of the paper is organized as follows. Section 2.2 introduces the most relevant features of the institutional setting. Section 2.3 describes our data. Section 2.4

outlines the empirical models. Section 2.5 presents our main results and investigates the underlying mechanisms. Section 2.6 includes a descriptive analysis at regional level and illustrates a theoretical framework. Section 2.7 concludes.

2.2 Background

Switzerland and the European Union are bound by deep economic and political relations that have intensified over the last decades, implying an increasing level of integration. Apart from trade and reciprocal market access, this cooperation concerns several policy fields including education, research, security and, most of all, the free movement of people and workers. Since the beginning of the 1990s, the progressive opening of the Swiss labor market to immigrants from EU countries has been the object of a long legislative process that induced a heated debate on the potential detrimental effects on natives' labor market outcomes.

Free access to the Swiss labor market for EU workers was introduced by the AFMP, one of the seven Bilateral Agreements between Switzerland and the EU.[2] The aim of the Agreements was to guarantee and promote reciprocal market access in several sectors after the Swiss voters rejected membership to the European Economic Area in 1992. They were announced by the Swiss government and the European Commission in June 1998, signed on June 21, 1999, approved by the Swiss electorate in a referendum in May 2000, and officially effective from June 1, 2002.

The implementation of the AFMP took place gradually. Before 1999, foreign workers in Switzerland were subject to yearly quotas set by the federal government and to the *priority requirement*, according to which an immigrant could be hired only if an equally qualified resident worker was not available. These restrictions were quite stringent and represented an issue for industries in need of foreign skilled workers (Afonso, 2004). Since 1999, however, these restrictions started to be loosened for immigrants from the EU, triggering a transitional phase characterized by a lower degree of tightness of yearly quotas, especially when hiring cross-border workers (Beerli et al., 2021). Indeed, a report published already in 2000 by the Canton of Ticino (Cantonal Statistical Office of Ticino, 2000) documents a remarkable increase in the number of incoming Italian cross-border workers in high-skilled occupations, especially in the tertiary sector. Such an inflow of newly hired cross-border workers materialized right after the introduction

[2]The other six agreements concern barriers to trade, public procurement markets, agriculture, overland transport, civil aviation and research.

of the AFMP in 1999, reversing a previously decreasing trend.

A key feature of the AFMP (Article 9) was the recognition of EU diplomas and professional certifications to encourage qualified immigration in Switzerland. It is worth mentioning here that in the Swiss setting regulated occupations requiring a qualification are not only high-skilled occupations as defined by the *International Standard Classification of Occupations* (International Labour Organization, 2008), but in some cases they might also include lower-skilled jobs, for instance in the food and accommodation sector.

The recognition of EU certifications was not uniform across the board. It was granted only to a number of precisely listed occupations that were heavily regulated before the reform. This implies remarkable differences across sectors in the exposure to the policy, depending on the share of treated occupations in each sector. We exploit this cross-sectoral variation for identification purposes.

More in detail, before the enactment of the AFMP, foreign workers who aimed at obtaining a job in a regulated occupation had to acquire a further occupation-specific Swiss qualification. The recognition of EU qualifications lifted this additional requirement. While all sectors were in principle equally affected by the abolition of quotas and priority requirements, sectors relying on a high share of previously regulated occupations were more exposed to the policy change. We exploit the differential exposure to the reform across sectors for identification and, indeed, find that sectors more intensive in occupations with now-recognized certifications experience a larger inflow of EU employees relative to less exposed sectors.

In 2004, two years after the full implementation of the AFMP, the Swiss government put in place a package of "accompanying measures" meant to limit the potential adverse effects of increased competition on the labor market. These measures aimed at strengthening the application of sector-level collective labor agreements that fix sectoral minimal wages and termination clauses. However, these measures are more likely to protect incumbent employees rather than new entrants in the labor market, who may instead face even stronger entry barriers.

The AFMP has been the object of a fierce opposition by some wings of the Swiss electorate (Mazzoleni and Pilotti, 2015). Such an opposition culminated in the referendum held on February 9, 2014, when voters approved the Federal Popular Initiative *Against Mass Immigration*. This initiative aimed at reintroducing quotas for immigrants and was accepted by 50.3% of Swiss voters, a share that reached 69.2% in the canton of Ticino.

However, while in 2016 the Swiss Parliament passed a law requiring employers to give priority to resident job seekers, quotas for EU workers were never reintroduced. Our analysis will focus on the time window between 1992 and 2008 to avoid not only the confounding effects of these developments in the immigration policy, but also the impact of the appreciation of the Swiss Franc during the Euro crisis, which altered cross-border workers' incentives.

2.3 Data

Our main empirical analysis leverages individual-level *social security* data for the canton of Ticino over the period 1992-2008. We complement this dataset with the *Swiss Labor Force Survey* to compute the share of treated occupations by sector. Additional data from the *Swiss Federal Statistical Office* (e.g., *Business Census* data on firms' workforce and *SHIS-Studex* data on tertiary education attendance) and from the *Cantonal Statistical Office of Ticino* (e.g., data on out-migration) will be used to offer a more complete picture of the labor market.

2.3.1 Social security data

This paper is based on Swiss administrative data released by the Institute of Social Security of the canton of Ticino (*Istituto delle Assicurazioni Sociali*). The dataset covers the quasi-universe of individuals paying contributions to the first pillar of the Swiss social security system since 1992, namely residents older than 20[3] and active workers regardless of their residence status, including cross-border workers.

We focus on Ticino, the only Italian-speaking[4] canton in Switzerland, because of its remarkably high degree of economic and social integration with the neighboring country of Italy (Decoville and Durand, 2019). In fact, Ticino is the Swiss canton characterized by both the highest share of non-Swiss employees[5] and the highest share of cross-

[3]Note that before January 1, 1997, residents in Switzerland without gainful employment were not subject to the obligation of contribution. Their contribution was only on a voluntary basis. The obligation introduced in 1997, however, does not affect our analysis as we focus on employed individuals and their transitions to inactivity. Reassuringly, there is no significant change in the share of employees becoming inactive in correspondence of this reform occurred in 1997 (see Section 2.6, Figure 2.6.3).

[4]While approximately 90% of Swiss citizens in Ticino speak Italian, German and French are ranked among the three main languages spoken only by 8% and 4% of them, respectively (Cantonal Statistical Office of Ticino, 2021).

[5]Appendix Figure B.1.1 reports the share of non-Swiss employees in the sixteen Swiss large labor market regions in 1998 and 2008. The labor market area of Lugano, where the vast majority of

border workers that exceeds 30% of the labor force (Swiss Federal Statistical Office, 2021). Indeed, the large wage differential between Switzerland and Italy represents a strong incentive for Italian residents close to the border to search for a job in Ticino. For instance, in 2002, employees' average annual earnings amounted to roughly 22,500 Euros in Italy and 77,200 Francs (i.e., 52,400 Euros) in Switzerland (OECD, 2023), a gap that is likely wider for high-skilled occupations requiring specific qualifications.[6]

For each individual in a given year between 1992 and 2008, our dataset reports whether the subject is an employee, a self-employed worker, or is inactive, a category that includes students, *long-term* unemployed,[7] people who choose not to enter the labor market (or who receive disability benefits), and early retirees. These subgroups are not explicitly distinguished in the data, but early retirement can be inferred from age (in Switzerland early retirement is allowed from age 58).

Our dataset includes personal information on sex, date of birth, and nationality. Unfortunately, the type of work permit for foreign workers (e.g., resident foreign national vs. cross-border worker) is not reported.[8] For every calendar year, the data contain active workers' annual earnings and the working period in months associated with each job. To avoid the potential impact on our estimates of extreme outliers in the values of annual earnings, we winsorize the top and the bottom percentiles of the distribution, by year and sex. When an individual has multiple jobs during the same year, we select the one associated with the highest annual income.

We express annual income in real terms at 1998 prices, using the Consumer Price Index released by the Swiss Federal Statistical Office. Differently from social security data available for the whole country, our canton-level dataset reports the sector according to an internal classification that we link to the two-digit *Swiss General Classification of Economic Activities* (NOGA, 2002 Nomenclature).

private sector firms in the canton is located, exhibits the highest share of non-Swiss employees in the country, reaching more than 65% in 2008. These figures are computed using Business Census data (Swiss Federal Statistical Office, 2016), which reports employment rate (but no wage rate) by sector, municipality, nationality, and gender.

[6]This large wage gap implies that, although the AFMP introduced a *mutual* recognition of qualifications, the outflow of Swiss workers towards Italy was very limited (see Beerli et al., 2021).

[7]In case of job loss, unemployment benefits can be received for at most two years. Over this period individuals are not observed in our dataset.

[8]We do not observe either posted workers who remain affiliated to their home-country social security system and work in Switzerland upon registration if the working period exceeds 8 days. According to the AFMP, posted workers are entitled to work in Switzerland for up to 90 days per calendar year only in the sectors of construction and civil engineering, hotels, restaurants and catering, cleaning, and itinerant retail trade. We acknowledge that these workers may play a role in explaining part of the effects on natives' labor market outcomes.

2.3.2 Assignment to treatment – Swiss Labor Force Survey data

Since our social security data do not include information on the level of educational attainment and on the specific occupation of each employee, we rely on the sector of the firm in which individuals are active to assign them to the treatment or control group. More specifically, in order to identify the sectors heavily exposed to the recognition of EU qualifications, we leverage additional data from the *Swiss Labor Force Survey* (SLFS), a representative survey covering the working-age (15+) resident population in Switzerland (Swiss Federal Statistical Office, 2022c). For each employee, the SLFS reports the occupation and sector of activity according to, respectively, the *International Standard Classification of Occupations* (ISCO-08) and the NOGA classification. Relying on the list of regulated occupations in Switzerland (State Secretariat for Education, Research and Innovation, 2022) involved in the enactment of the AFMP, we identify the occupations (ISCO-08) affected by the recognition of qualifications released by EU countries. Then, we compute the share of individuals employed in a "treated" occupation within each sector to evaluate its degree of exposure to the reform. To be consistent with the sample selected for our empirical investigation (more on this below), we focus on private sector male employees active in Ticino over the period 1996–2008.[9]

From this procedure, we obtain a bimodal distribution of shares of workers employed in treated occupations. This allows us to clearly distinguish between sectors with low and high shares (on average, 16.41% vs. 47.55%). Henceforth, we will refer to these two groups as, respectively, *untreated* and *treated* sectors. Appendix Table B.2.1 provides the full list of treated and untreated sectors in our social security data, showing for each of them the share of employees holding treated occupations according to the SLFS, as well as the evolution over time of the share of Italian employees. Treated sectors include chemical industries, legal assistance, engineering and architecture, communication and transports, hotels and restaurants, IT and auxiliary services for trade (e.g., accounting). As robustness check, we will also investigate the role of treatment intensity to verify whether the effect of the policy is larger in sectors with a higher share of treated occupations.

Appendix Table B.2.2 examines whether the proportion of treated occupations within sectors changed over time, testing for convergence dynamics driven by the po-

[9] Ideally we would like to focus on the pre-reform period, but before 2002 the SLFS is not representative at canton level due to the low number of observations. Reassuringly, our results are robust to the use of a treatment definition based on private sector male employees active in Switzerland in the pre-reform period.

tential expansion of such occupations after the reform. The overall stability of these shares suggests that there is no evidence of any relevant convergence pattern.

The degree of mobility across economic sectors is quite limited, as the average annual share of employees changing sector is 6.11% (ranging between 4.2% and 7.2% over the period 1992–2008). Moreover, the average share of individuals who change firm every year, which represents an upper bound for mobility across occupations, amounts to 8.86% (ranging between 6.10% and 11.61%).

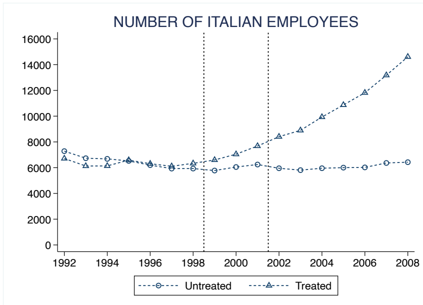
2.3.3 Sample selection and descriptive evidence

Since a substantial share of Swiss females and of public sector employees are part-time workers, we exclude them from our analysis. In their case, indeed, the lack of information on the number of hours in our data is problematic because we cannot distinguish changes in hours worked from changes in hourly wages.[10] Additionally, due to pervasive regulation, public sector wage dynamics are likely different from private sector dynamics.

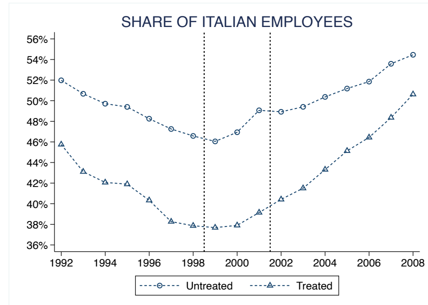
Finally, since our data include individuals affiliated to the cantonal office that collects first pillar contributions in Ticino, we cannot observe workers who belong to other compensation offices. In particular, we are not able to cover the banking and insurance sector, which represented approximately 9% of private sector male employees in 1998, a share that has largely decreased over time. At the same time, the share of Swiss employees in this sector decreased from 85% in 1998 to 80% in 2008 (*Business Census* data). According to the SLFS data, the banking and insurance sector would belong to the treated group. While we cannot state a priori whether the effect of the AFMP on this sector would be homogeneous with the other treated sectors, the relatively low share of employees in this sector suggests that its inclusion should not affect our results significantly.

Figure 2.3.1 shows the evolution over time of the absolute number (panel 2.3.1a) and share (panel 2.3.1b) of Italian employees for treated and untreated sectors. The number of Italian employees in treated sectors increased sharply after 1999, doubling in size in 2008 compared to 1998, while it remained constant in untreated sectors (panel a). The

[10] According to our calculations based on Business Census data (Swiss Federal Statistical Office, 2016), not only the participation to the labor force of Swiss women was rather low in Ticino in 1998 ($\approx$ 48%), but roughly 25% of active women worked part-time at a rate between 50% and 90%, and almost 20% of them at a rate below 50%. On the contrary, 94% of male employees held full-time jobs. See Buchmann et al. (2010) for a review of the structural factors driving women's employment decisions in Switzerland.



(a)



(b)

Figure 2.3.1: Evolution of Italian employees in treated and untreated sectors

Notes: This figure shows the evolution over time (1992-2008) of the absolute number (panel a) and share (panel b) of Italian male employees in private sector firms with at least two employees in the canton of Ticino. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

share or Italian employees in both treated and untreated sectors has sizeably grown after the AFMP was signed, reversing a previous decreasing trend (panel b). Because of the recognition of EU certifications, this increase has been far more pronounced in treated sectors, where the share of Italian employees was initially lower due to the restrictions in place (Section 2.2). Appendix Table B.2.3 displays the evolution of the share of Italian employees in treated and untreated sectors by age group. It also presents the summary statistics for our main variables (real monthly wage, entry wage after changing firm, and probability of transition to inactivity).

2.3.4 Additional data

To compare young Swiss citizens entering the labor market in Ticino before and after the reform, we leverage additional data on education and migration decisions. We rely on the *SHIS-Studex*[11] database (Swiss Federal Statistical Office, 2023) to have information on the annual number of male students from Ticino attending Swiss universities, including vocational ones. In addition, we use statistics from the Cantonal Statistical Office (*USTAT*) to examine the annual share of residents moving to other Swiss cantons or abroad, by sex, age, and nationality.

[11]Note that the individual-level information in this dataset cannot be merged with our social security data, as the linkage through the individual social security ID is possible only after 2012.

2.4 Empirical Modelling

We study the impact of the policy adopting a difference-in-differences (DiD) approach that compares the evolution of a number of labor market outcomes across sectors that are differentially affected by the recognition of EU qualifications.

2.4.1 Baseline dynamic DiD model

To assess the salience of the reform, we first investigate the impact of the policy on the firm-level share of Italian employees in firms located in Ticino, estimating the following model:

$$y_{ft} = \alpha_f + \sum_{k=1992}^{2008} \pi_k \, treated_f \cdot \mathbb{1}[t = k] + \chi_d + \mu_t + \epsilon_{ft} \tag{2.1}$$

where y_{ft} is the share of Italian employees, overall or by age group (18–29; 30–49; 50–64), working in firm f and year t.[12] We include administrative districts fixed effects (χ_d) to account for geographical time-invariant features, in particular distance from the Italian border,[13] year dummies (μ_t) that capture aggregate fluctuations, and firm fixed effects (α_f) that control for time-invariant firms' characteristics affecting the propensity to hire foreign employees and potentially correlated with the treatment status. The error term ϵ_{ft} captures unobservable time-varying shocks to firm f. Standard errors are two-way clustered, at sector and at year level.

The dummy variable $treated_f$ takes value one if firm f belongs to a treated sector and is further interacted with an indicator variable $\mathbb{1}[t = k]$, one for each year t, excluding the reference year 1998 – the last year before the announcement of the AFMP, which led to a gradual loosening of restrictions on the hiring process of EU workers. Thus, the coefficients π_ks ($k = 1992, ..., 1997, 1999, ..., 2008$) measure the (potentially time-varying) impact of the policy.

We next move to a worker-level analysis and investigate the effect of the policy on Swiss employees' real wages. We estimate the following model:

[12] When we estimate model (2.1) breaking down the share of Italian employees by age group, the outcome variable is the ratio of the number of Italian employees of a specific age group to the total number of employees in firm f in year t.

[13] The canton of Ticino consists of eight districts, three of which (Locarno, Lugano, Mendrisio) share borders with Italy, while the other five (Bellinzona, Blenio, Leventina, Riviera, Vallemaggia) are smaller and less populated. At the beginning of the 1990s, more than 70% of firms were already located in the three districts at the border with Italy; this proportion reached 80% in 2008.

$$w_{ist} = \alpha_i + \sum_{k=1992}^{2008} \beta_k \, treated_{it} \cdot \mathbb{1}[t = k] + \chi_d + \lambda_s + \mu_t + f(age) + \epsilon_{ist} \tag{2.2}$$

in which the outcome variable w_{ist} is the log of the real monthly wage of employee i in sector s in year t. As discussed in Section 2.3, we assign each individual to the *treatment status* depending on the employing firm's sector, so $treated_{it}$ takes value one if employee i works in year t in a treated sector.

We include district fixed effects (χ_d), sector fixed effects (λ_s) to account for time-invariant differences across sectors, year dummies (μ_t), and individual fixed effects (α_i) to account for time-invariant individual characteristics (e.g., ability) influencing wages and potentially correlated with the treatment status. This limits the extent of the omitted variable bias and helps interpreting β_k as the actual effect of the policy. Finally, $f(age)$ is a quadratic polynomial for age. Robust standard errors are two-way clustered at sector and at year level.

To explore the potential heterogeneity of the effect, we estimate equation (2.2) separately for different subsamples of native employees, depending on their age group (18-29; 30-49; 50-64) in each year t.

The key underlying assumption is that trends in the outcome of interest for treated and untreated sectors would be identical in the absence of treatment. While this assumption is not directly testable, our dynamic specification allows us to formally test the presence of parallel trends in the pre-policy period. Moreover, the unconditional comparison of the two wage series for treated and untreated sectors (Appendix Figure B.1.2) suggests that the two groups are also very similar in levels, making the parallel trend assumption more credible.

2.4.2 "Frozen" model

To further study the heterogeneous effect of the reform, we differentiate between employees active before the policy change and those hired afterwards. Hence, we estimate a version of model (2.2) that focuses on incumbent employees active in 1998. In this specification, the variable $treated_{it}$ is substituted by the time-invariant variable $treated_i$, which takes value one or zero depending on the sector in which the employee was active in 1998. Since movements in and out of treatment are not frequent (on average, 4% of employees every year) and do not affect our estimates (see robustness checks below), any differences from baseline results are driven by new-entrant employees rather than by having fixed incumbents' sector in 1998.

2.4.3 Static DiD model

We complement our worker-level investigation of the effects of the AFMP on native employees' wages and study its impact on the probability of transiting to inactivity by estimating the following *static* difference-in-differences specification:

$$\begin{aligned} y_{ist} = \alpha_i + \delta_1 treated_{it} \times transition_t + \delta_2 treated_{it} \times post2002_t \\ + \chi_d + \lambda_s + \mu_t + f(age) + \epsilon_{ist} \end{aligned} \tag{2.3}$$

in which the two time dummies $transition_t$ and $post2002_t$ identify the transition phase between 1999 and 2001 and the post-policy period since 2002, respectively. In this model, the outcome variable y_{ist} can be either represented by employees' real wages – like in model (2.2) – or by employees' probability of becoming inactive (i.e., facing long-term unemployment or remaining out of the labor force in Ticino).

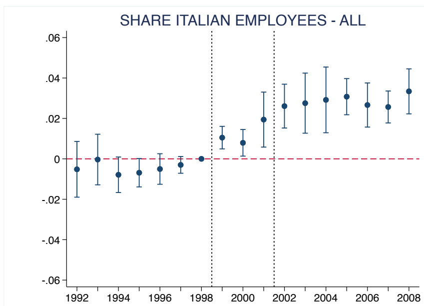
In the latter case, we estimate a linear probability model in which y_{ist} is a dummy variable taking value one if employee i in sector s and year t becomes inactive in year $t+1$. Differently from the model for wages, this model cannot include individual fixed effects because of the relatively low number of transitions out of employment.

We also estimate a multinomial logit model to distinguish between private sector employees' likelihood of becoming inactive, leaving the dataset,[14] or moving to the public sector. Appendix B.3 provides more details about this specification. It is worth mentioning here that, while we can study employees' probability of either becoming inactive in Ticino or leaving the dataset, the probability of being re-employed for displaced workers cannot be measured reliably. Indeed, the available data do not allow to track individuals who relocate to be employed outside the canton of Ticino or find a job in sectors not covered by the dataset (e.g., banking and insurance).

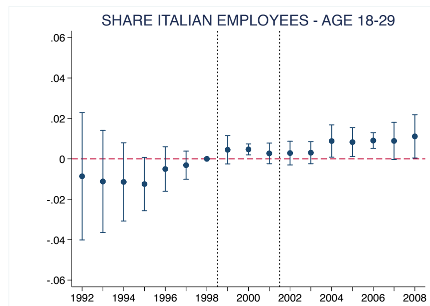
[14] We define the occurrence of an *exit* when an individual leaves the dataset and does not enter again within three years. Indeed, we do not observe individuals who receive unemployment benefits for up to two years after the job loss. Excluding subjects who enter economic sectors not covered by our data, the vast majority of exits are represented by (intercantonal) out-migration.

2.5 Results

Figure 2.5.1 shows the dynamic impact of the policy on the share of Italian employees in firms, reporting the coefficients of our multi-period difference-in-differences model (2.1) with 95% confidence intervals. Panel (a) considers the overall firm-level share of Italian employees, while panels (b)–(d) examine the proportion of Italian employees in each age group (18-29; 30-49; 50-64) relative to the total workforce of the firm.



(a)



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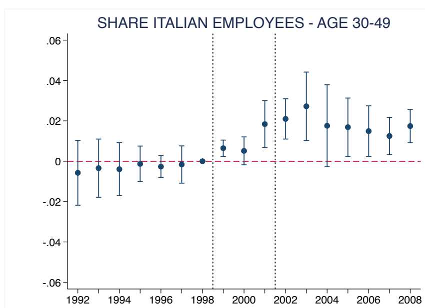

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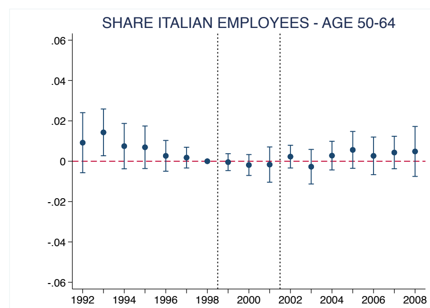


(d)

Figure 2.5.1: Share of Italian employees in firms – Dynamic DiD model

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.1). Panel (a) refers to the overall share of Italian male employees in private sector firms with at least two employees, while panels (b)–(d) refer to the proportion of Italian employees belonging to different age groups (18–29; 30–49; 50–64) on the total number of employees in a firm. Each graph shows the estimates of the coefficients π_k (k = 1992,..., 1997, 1999, ..., 2008) with confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All specifications include district, year, and firm fixed effects. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

The recognition of EU qualifications led to a large increase in the share of Italian employees (panel a), especially young (panel b) and middle-aged (panel c), while the increase for age group 50–64 (panel d) is negligible. While the coefficients in panels (b) and (c) are similar in magnitude, the average initial share of young Italian employees in treated firms was almost four times lower than the share of their middle-aged counterparts, as displayed in the last two rows of Table 2.5.1. Hence, the effect of the policy was far larger for the youngest age group ($\approx$ 23% of the pre-policy value). Table 2.5.1 presents the estimates from the *static* version of equation (2.1), confirming the large increase in the share of young and middle-aged employees (Columns 2 and 3).

Table 2.5.1: Share of Italian employees in firms (1992-2008)

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
treated $\times$ transition	0.017***	0.010*	0.012*	-0.006
	(0.004)	(0.006)	(0.006)	(0.005)
treated $\times$ post2002	0.032***	0.013***	0.021**	-0.002
	(0.005)	(0.004)	(0.008)	(0.006)
N	84955	84955	84955	84955
Mean in 1998 (T)	31.49%	4.02%	18.51%	8.95%
Mean in 1998 (U)	38.11%	5.68%	19.73%	12.70%

Notes: This table shows the estimates of the difference-in-differences coefficients of a *static* version of model (2.1). Column (1) reports the estimates for the full sample of male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). All models include district, year, and firm fixed effects. Robust standard errors are two-way clustered at sector and year level. The last two rows display the average shares of Italian employees by age group in 1998 in treated (T) and untreated (U) sectors, respectively. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

In what follows, we investigate the effect of this increased competition from qualified workers on natives' wages. Figure 2.5.2 presents the dynamic effect of the policy on the real wages of Swiss employees. Panel (a) shows that the policy had an overall positive, albeit not statistically significant, impact. This result, however, hides a remarkable heterogeneity across age groups. The effect was negative for young native employees aged 18–29 (panel b) while it was positive for employees aged 30–49 (panel c). The effect then vanished when considering older individuals above age 50 (panel d). It is worth noting that the coefficients in the pre-treatment period are always close to zero and never statistically significant. As we will discuss later, the negative effect borne by young Swiss employees is driven by a reduction in the entry wages offered to those entering the labor market after 1999. This effect materializes relatively soon after the announcement of the AFMP in 1998. As anticipated in Section 2.2, since 1999 restrictions on the hiring process of cross-border workers, especially in high-skilled sectors, were progressively loosened (Beerli et al., 2021; Cantonal Statistical Office of Ticino, 2000).

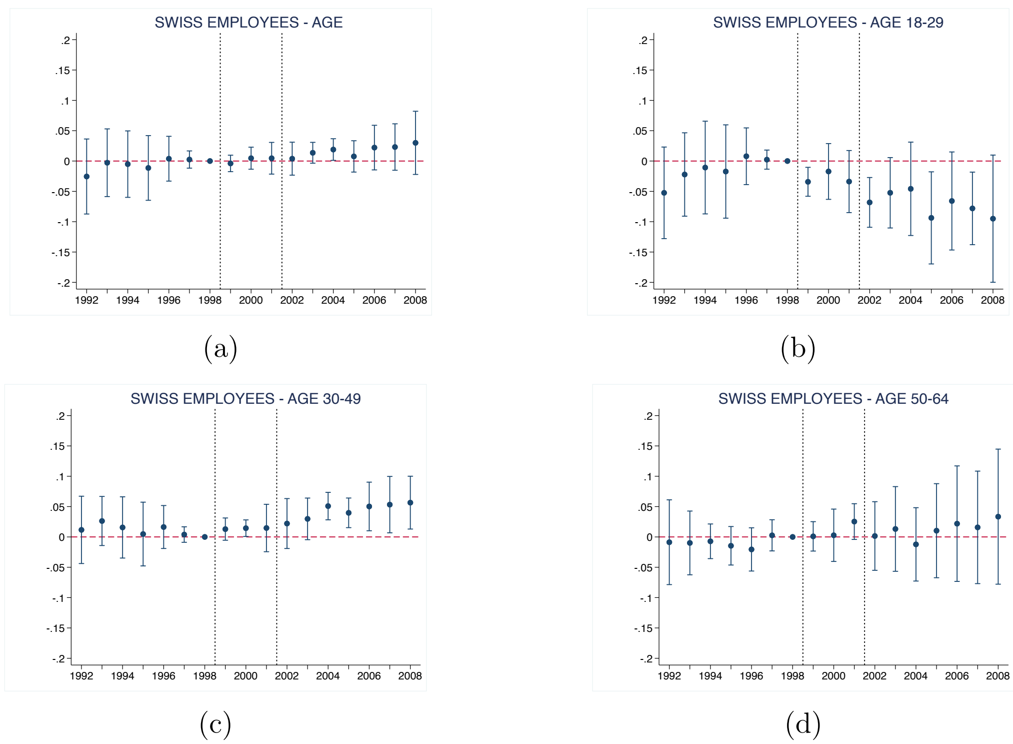


Figure 2.5.2: Swiss employees' (log) real monthly wages – Dynamic DiD model

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2). Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) refer to different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

The estimates from model (2.3) in Table 2.5.2 confirm a wage loss of 6 percentage points burdened by young (18–29) employees (Column 2) and a wage gain of more than 3 percentage points for middle-aged (30–49) employees (Column 3). The point estimates obtained from the static specification summarize well the estimated effects in the dynamic specification, but standard errors tend to be larger. This is likely the result of the different reference periods, namely the whole 1992–1998 pre-policy period in the static model instead of year 1998 only in the dynamic specification.

Table 2.5.2: Swiss employees' (log) real monthly wages (1992-2008)

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
treated × transition	0.006	-0.023	0.005	0.014
	(0.022)	(0.032)	(0.020)	(0.021)
treated × post2002	0.020	-0.062*	0.031	0.013
	(0.028)	(0.035)	(0.028)	(0.041)
N	243209	68542	122407	47705
Mean in 1998 (T)	3.56	3.20	3.70	3.75
Mean in 1998 (U)	3.65	3.27	3.82	3.88

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) for real wages. Column (1) reports the estimates for the full sample of Swiss male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The last two rows display the average (log) real monthly wages of Swiss employees by age group in 1998 in treated (T) and untreated (U) sectors, respectively.
Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

In Table 2.5.3, we then focus on the impact of the policy on employees' probability of becoming inactive, reporting the estimates from our linear probability model (2.3). The negative coefficient displayed in Column 4 shows that the AFMP has led Swiss employees aged 50-64 to be less likely to become inactive. On the contrary, young native employees have experienced an increase in their likelihood to leave the labor force in Ticino (Column 2).

However, while these estimates measure the impact of the policy change on employees' probability of becoming inactive without leaving the canton of Ticino, a reliable estimate of the overall probability of being re-employed for displaced workers cannot be obtained. Indeed, individuals who either relocate to other Swiss cantons or find a job in sectors not covered by the dataset (e.g., banking and insurance) are not observed (see Section 2.3).

Table 2.5.3: Swiss employees' probability of inactivity (1992-2008)

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
treated × transition	-0.002**	0.004*	-0.003**	-0.004
	(0.001)	(0.002)	(0.001)	(0.002)
treated × post2002	-0.000	0.009**	-0.000	-0.006*
	(0.001)	(0.004)	(0.001)	(0.003)
N	227814	61428	119710	46676
Mean in 1998 (T)	1.73%	2.61%	1.00%	2.46%
Mean in 1998 (U)	1.11%	1.10%	0.64%	2.29%

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) for the probability of becoming inactive. Column (1) reports the estimates for the full sample of Swiss male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). All models include sector, district, and year fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The last two rows display the average shares of Swiss employees becoming inactive (or leaving the dataset) by age group in 1998 in treated (T) and untreated (U) sectors, respectively. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

2.5.1 Incumbent vs. new-entrant native employees

We now turn to our 'frozen' specification of model (2.3), which fixes employees' treatment status and age group in 1998, focusing on incumbent individuals already active in the local labor market before the reform.

Table 2.5.4 presents the results for incumbent employees' wages (Panel A) and for their probability of inactivity (Panel B). The coefficients reported in Panel A broadly confirm the findings presented in Figure 2.5.2 and Table 2.5.2. There is however one remarkable exception for young employees, as the negative effect disappears and even turns positive, although not statistically significant (Column 2).[15] Besides, the es-

[15] Appendix Figure B.1.3 shows the estimates from the corresponding 'frozen' version of model (2.2).

timates from our linear probability model reported in Panel B suggest that young incumbents have also benefited from a reduction in the likelihood of inactivity.

Since the difference with respect to the baseline model lies in the exclusion of employees entering the labor market after 1998, this result suggests that the adverse consequences of the policy change have been borne by young native new entrants. Actually, Figure 2.5.3 shows a reduction in their entry wages in treated sectors since 1999. As we will discuss, this drop is explained not only by increased wage competition,[16] but also by compositional changes in the profiles of young new entrants induced by the policy.

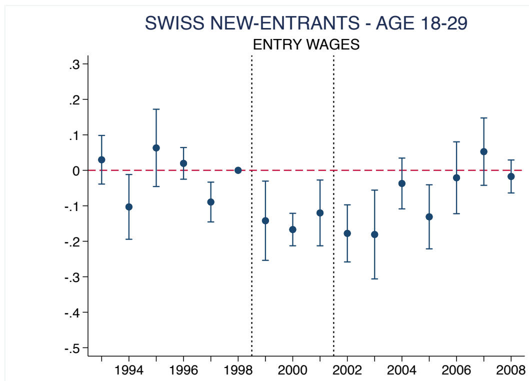


Figure 2.5.3: Young Swiss employees' entry (log) real monthly wages

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2) for the cross-section of young Swiss employees observed in their first year in the labor market. It reports the estimates of the coefficients β_k (k = 1993,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. The model includes sector, district, and year fixed effects, plus a linear and a quadratic age term. Since in this cross-sectional analysis each individual is considered only once, when entering the labor market, individual fixed effects are dropped. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

To further test the hypothesis of the incumbent advantage, we repeat the analysis for Italian employees (see Appendix Table B.2.4 and Appendix Figure B.1.4). The results suggest that incumbent Italians' labor market outcomes were not harmed. This is not surprising because they could take advantage of acquired experience and are also likely to be positively selected, as they were required to obtain an additional Swiss qualification to access treated sectors before the policy change.

[16]Note that the gap with untreated sectors begins fading away after 2004, when the government introduced the accompanying measures meant to limit the downward pressure on wages driven by increased wage competition (see Section 2.2).

Table 2.5.4: Incumbent Swiss employees' labor market outcomes (1992-2008)

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
Panel A: (Log) real monthly wages				
treated × transition	0.010	0.014	0.011	0.016
	(0.021)	(0.035)	(0.022)	(0.021)
treated × post2002	0.030	0.046	0.030	0.035
	(0.026)	(0.033)	(0.027)	(0.047)
N	148167	39073	80556	28538
Mean in 1998 (T)	3.56	3.20	3.70	3.75
Mean in 1998 (U)	3.65	3.27	3.82	3.88
Panel B: Probability of inactivity				
treated × transition	-0.007**	-0.010***	-0.005	-0.006
	(0.003)	(0.004)	(0.004)	(0.005)
treated × post2002	-0.007**	-0.008***	-0.006	-0.004
	(0.003)	(0.001)	(0.003)	(0.009)
N	154382	39805	84230	30347
Mean in 1998 (T)	1.73%	2.61%	1.00%	2.46%
Mean in 1998 (U)	1.11%	1.10%	0.64%	2.29%

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) when treatment status and age are fixed in 1998 ("frozen" model). Column (1) reports the estimates for the full sample of Swiss male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). Panel A refers to wages, while panel B to the probability of becoming inactive. All models include sector, district, year, and (only for wages) individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The last two rows of Panel A display the average (log) real monthly wages of Swiss employees by age group in 1998 in treated (T) and untreated (U) sectors, respectively. The last two rows of Panel B display the average shares of Swiss employees becoming inactive in Ticino. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

2.5.2 The role of incumbents' individual ability and firm-to-firm movers

To shed further light on the mechanisms behind the wage gains experienced by native incumbent employees, we investigate more in detail the role of ability. For Swiss employees active in 1998, i.e. for incumbent native workers, we first estimate individual fixed effects from a regression of (log) real wages on sector, year, district, and individual fixed effects, plus a quadratic age term, over the pre-policy period (1992–1998). Individual fixed effects are derived separately for age groups, conditional on age in 1998. For each age group, we define as high-ability employees those belonging to the top quintile of the fixed effects distribution.[17] We then estimate a triple interaction version of equation (2.3) on the sample of incumbent native workers for which we are able to get the individual fixed effects from the above regression, adding a further interaction with a dummy variable for high ability. Table 2.5.5 shows that statistically significant and economically relevant wage gains are concentrated among middle-aged and, to a lesser extent, young incumbent native employees with high ability.[18] On the contrary, the wages of Swiss employees with a low level of ability have remained unaffected.

We next explore whether the wage effects of the policy differ between incumbent native employees who have moved to a different firm and those who have not. Appendix Table B.2.6 suggests that, while there are no statistically significant wage effects for employees remaining at the same firm where they were active in 1998 (Panel A), the policy has led to sizeable gains for firm-to-firm "movers" aged 30–49 and 50–64 (Panel B), namely those with more experience in the local labor market. This positive effect may also reflect, at least partially, a higher degree of screening by firms, as increased competition might induce them to select the most skilled and productive native employees.

2.5.3 The profile of young Swiss new entrants

Since the wage loss and the increased inactivity for young Swiss employees is driven by new entrants in the labor market after the policy change (as in Figure 2.5.3), we now investigate whether compositional changes, such as changes in the age and education of new-entrants, might explain, at least partly, our results.

We start our investigation from Figure 2.5.4 (panel a), which shows the age profile of young Swiss new entrants. While new entrants in treated sectors are on average older than new entrants in untreated sectors, there is evidence of a more pronounced decline in the entry age in treated sectors after 1999: the average entry age in treated sectors, which was stable at roughly 23 until 1999, sharply decreased to 22 within the

[17] This should approximately capture the fraction of the Swiss population with a tertiary-level degree or a professional qualification as, according to Census data, in year 2000, about 22% of the Swiss population had either tertiary education or professional qualification (`https://www.bfs.admin.ch/bfs/en/home/basics/census.assetdetail.1021397.html`).

[18] Appendix Table B.2.5 shows that estimates do not change when high-ability employees are defined as those belonging to the top tercile of the predicted distribution of individual fixed effects.

Table 2.5.5: Incumbent Swiss employees' (log) real monthly wages by ability (1992-2008)

	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)
treated × transition	-0.006	0.018	0.022
	(0.047)	(0.022)	(0.032)
treated × transition × high	0.012	0.095***	0.043
	(0.045)	(0.032)	(0.070)
treated × post2002	0.001	0.036	0.072
	(0.037)	(0.045)	(0.071)
treated × post2002 × high	0.127*	0.082***	-0.047
	(0.063)	(0.015)	(0.048)
N	33510	76341	27530
Mean in 1998 (T)	3.31	3.78	3.83
Mean in 1998 (U)	3.38	3.85	3.92

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) when treatment status and age are fixed in 1998 ("frozen" model). In these models we control for high ability by considering the top quintile of the predicted distribution of individual fixed effects (between 1992 and 1998) for Swiss employees active in 1998. Columns (1)-(3) report the estimates for Swiss male employees in private sector firms with at least two employees, distinguishing between different age groups (18–29; 30–49; 50–64), fixed in 1998. All models include sector, district, and year fixed effects, plus a linear and a quadratic age term and a dummy for high ability. Robust standard errors are two-way clustered at sector and year level. The last two rows display the average (log) real monthly wages of Swiss employees by age group in 1998 in treated (T) and untreated (U) sectors, respectively. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

subsequent two years. As the initial difference in levels between the two groups can be explained by the higher level of education of employees in treated sectors, one might be tempted to interpret the decline in the age of entry in the labor market observed in treated sectors after the policy change as evidence of a decline in the level of education of the new entrants in those sectors. However, this interpretation is in contrast with the rise in the number of male students from Ticino attending tertiary education in Swiss universities (panel b), which started in 1997 and was likely triggered by the contemporaneous increase in the supply of educational services.[19]

[19] Precisely in 1997 vocational universities were established in the Swiss education system (Bächli and Tsankova, 2023). These universities, also known as *universities of applied sciences*, offer vocational training in several fields (e.g., engineering, IT, chemistry, business, healthcare...), emphasizing the

The out-migration patterns for age groups 18-24 and 25-29 reported in panel (c) is, instead, consistent with the declining age (and wages) of new entrants. The figure clearly shows that the proportion of young male residents aged 25–29 moving from Ticino to other cantons started to increase in 1999, after exhibiting a declining trend over the previous years. This suggests that more educated native citizens, who would have otherwise entered the labor market upon completing their tertiary education, may have instead moved to other cantons. On the opposite, there is no evidence of outflow migration for younger male residents (aged 18–24). Finally, panel (d) shows no evidence of increased migration abroad.

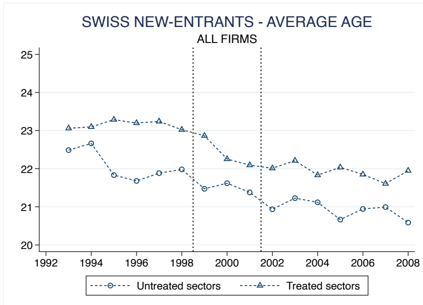
All in all, Figure 2.5.4 indicates that the wage losses experienced by young native new entrants after the introduction of the AFMP may partly reflect compositional changes, likely triggered by the policy change. Despite the increasing number of students attending tertiary education, the growing share of young native citizens aged 25–29 – likely with tertiary education – that relocate to other cantons implies that young Swiss employees entering the labor market in Ticino are on average younger and less likely to have achieved tertiary education.

We attempt to measure the extent to which the decline in native young employees' average entry wages reported in Figure 2.5.3 after 1999 can be attributed to changes in age composition. To this aim, we first estimate the coefficients of our difference-in-differences model on Swiss employees' entry wages separately for each specific age cohort between 19 and 29. We then compute the counterfactual coefficient that would have been observed in the year 2000 for the age group 18-29 absent compositional changes, by averaging the age-specific coefficients keeping the share of entrants belonging to each age cohort at the 1998 level. According to this back-of-the-envelope calculation, the magnitude of the coefficient would have decreased (in absolute value) from -0.182 to -0.167, suggesting that approximately 8.5% of the overall decline in entry wages can be attributed to the change in the age composition due to the policy.

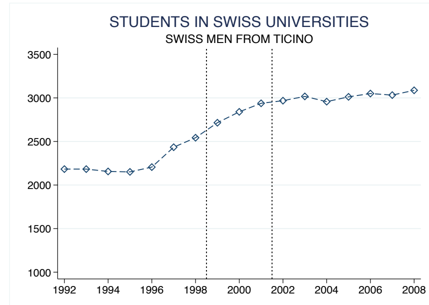
2.5.4 Robustness checks and extensions

As a first robustness check, we estimate equation (2.2) excluding employees who change treatment status. The coefficients in Appendix Figure B.1.5 are consistent with those reported in Figure 2.5.2, although sometimes less precisely estimated. Thus, our baseline results are not driven by employees self-selecting into treated sectors.

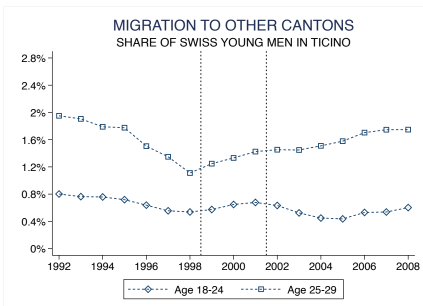
acquisition of industry-specific practical skills. One of them was established in Ticino.



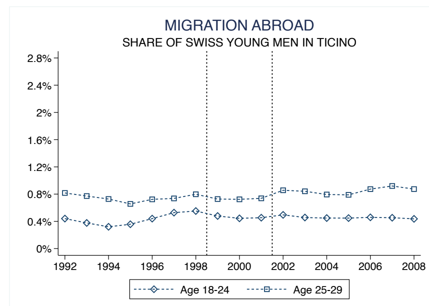
(a)



(b)



(c)



(d)

Figure 2.5.4: Young native citizens' entry age in the labor market, tertiary education attainment, and migration decisions (1992–2008)

Notes: Panel (a) shows the average age of Swiss young individuals entering the labor market in Ticino for the first time in treated and untreated sectors. Panel (b) reports the number of male students from Ticino attending tertiary education in Swiss universities, including vocational universities. Panels (c) and (d) display the share of Swiss male residents in Ticino who move, respectively, to other Swiss cantons or abroad, distinguishing age groups 18–24 and 25–29. In each panel, the first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

Given that our data do not track movements across occupations, we check that observed effects are not due to changes in the degree of within-sector mobility by replicating the analysis excluding all individuals who changed firm over time. The estimates presented in Appendix Figure B.1.6 are in line with those in Figure 2.5.2, especially for young native employees. The positive effect for middle-aged workers tends instead to become less sizeable, a result consistent with the fact that their wage gains are mostly explained by firm-to-firm movements (Appendix Table B.2.6).

In Appendix Figure B.1.7 we report the estimates of our dynamic difference-in-differences model when we use as treatment variable the continuous share of treated occupations in each sector, rescaled by their interquartile range to make coefficients easier to interpret. Different from the baseline specification with binary treatment, the figure shows evidence of a positive pre-trend for young and old employees.[20] This is not particularly worrying as, right after the policy, the pre-trend flattens out (50–64 age group) or even turns negative (18–29 age group). Thus, the pre-trend does not drive our results: it rather hides it. To clean up the effect of the policy from the differential pre-trend across treated and control sectors, we use a two-step procedure: *i*) we first regress log wages on a linear trend interacted with the continuous treatment variable (controlling for a quadratic polynomial in age, as well as for year, sector, district, and individual fixed effects) using only the pre-policy period (1992–1998); *ii*) we then remove the differential pre-trend from log wages and estimate the event study model again.[21] Figure B.1.8 reports the results of this procedure for the two age groups (young and old) for which we observed evidence of differential pre-trends. Our main result of a negative effect of the reform on the wages of native employees aged 18–29 is confirmed once we account for the differential trend showing up before the enactment of the AFMP. Also, the policy did not significantly impact the trend of wages for older individuals above age 50, although point estimates tend to be negative after 2004.

Next, we change our main specification and estimate equation (2.2) including firm (instead of sector) fixed effects. Results in Appendix Figure B.1.9 largely confirm our findings, in particular the wage losses borne by young native employees and the wage gains obtained by their middle-aged counterparts.

We also estimate equation (2.2) for Swiss employees' total real average monthly earnings, instead of focusing only on the monthly wage associated to the main job. Despite the additional noise potentially introduced by including short contracts and intermittent jobs, results in Appendix Figure B.1.10 are largely consistent with our main findings in Figure 2.5.2. Besides, in Appendix Figure B.1.11 we show evidence of an increase in the average worked months for middle-aged and young employees, although in the latter case the pattern is less clear, while we do not find any effect for older individuals.

To reinforce our experience-based interpretation of the differences in the wage effects of the policy across age groups, we estimate equation (2.3) splitting the sample of employees according to years of experience in Ticino rather than age.[22] Appendix

[20]The differential pre-trend is driven by the IT sector which was booming during the 90's.

[21]Since we do not have a staggered design, we cannot include this pre-trend in the main model à la Dobkin et al. (2018) because of the collinearity between event time and calendar time. So, we estimate it on the pre-policy period as described above.

[22]Experience is measured counting the years in which an employee is recorded in our dataset.

Table B.2.7 confirms that the gains are concentrated among employees with a larger experience acquired on the local labor market, while wage losses are borne by less experienced native employees.

As far as the effect of the AFMP on native employees' labor market status is concerned, Appendix Table B.2.8 reports estimates from a multinomial logit model that studies the probability of remaining employed, becoming inactive (i.e., long-term unemployed or out of the labor force in Ticino), leaving the dataset, or moving to the public sector (see Appendix B.3). Results are consistent with those obtained from the OLS model and presented in Table 2.5.3.[23] For young native employees, we now estimate a statistically significant reduction in the probability of remaining employed, driven by an increase in both the likelihood of inactivity and, to a larger extent, of leaving the dataset as a result of out-migration.[24]

We strengthen our evidence on the channel through which Swiss employees enjoy wage gains by estimating equation (2.3) on the first wages earned by firm-to-firm movers. Results in Appendix Table B.2.9 are consistent with those in Appendix Table B.2.6 and show that the wages earned by middle-aged native employees upon switching firm increased after the reform in treated relative to untreated sectors.[25]

Finally, we estimate a version of model (2.3) that accounts also for firms' distance from the Swiss-Italian border, using a triple difference-in-differences estimator.[26] As anticipated in Section 2.3, the majority of private sector firms in Ticino are close to the border with Italy, so we use a threshold of 5 kilometers, which leaves 54% of observations in the border area. The results of our triple difference-in-differences model for native employees' wages and probability of inactivity are presented in Appendix Table B.2.10. In line with the findings of Beerli et al. (2021), our estimates show that wage gains for employees aged 30–49 in treated sectors have been far larger close to the border (Panel A, Column 3). Moreover, both the drop in real wages (Panel A, Column 2) and the increase in the likelihood of inactivity (Panel B, Column 2) borne by young Swiss (new-entrant) employees have been more pronounced in border municipalities.

[23] Notice that, by splitting age groups 50–57 and 58–64, we can attribute the reduced likelihood of inactivity to a lower propensity of opting for early retirement in the latter group.

[24] While the probability of switching from private to public sector does not change, native citizens may still have become more likely to directly enter the labor market in the public sector.

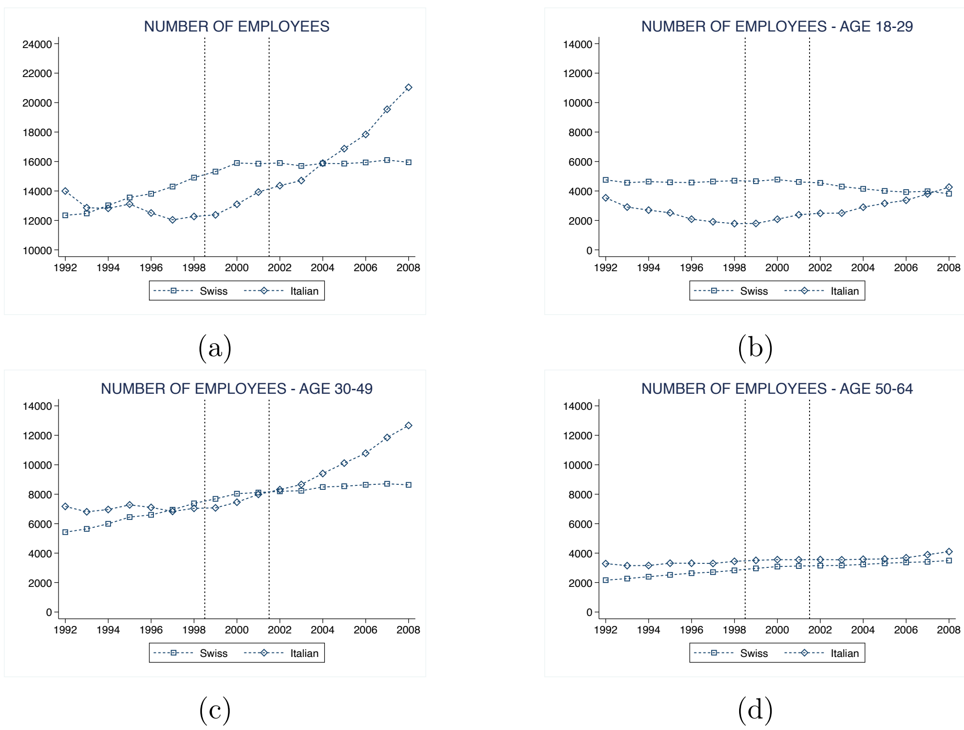
[25] Notice that, since the model includes individual fixed effects, the coefficient is identified on the subsample of employees that change firm at least twice.

[26] We rely on geodata released by the Swiss Federal Office of Topography (2022), which allow us to compute the distance between the centroid of the municipality and the nearest border crossing office for 96.5% of observations in our sample.

2.6 Discussion

2.6.1 The macro trends

To provide a more comprehensive interpretation of our results, this section presents descriptive macro evidence of the labor market trends in Ticino over the period in which the Bilateral Agreements were enacted. We first show how the reform affected the size and nationality composition of the workforce. We then discuss the behaviour of real wages and of the share of employees becoming inactive by age group.



(a) (b) (c) (d)

Figure 2.6.1: Number of employees by nationality and age group

Notes: This figure shows the evolution over time (1992-2008) of the number of male employees in private sector firms with at least two employees. Each panel compares the number of Swiss and Italian employees. Panel (a) refers to the whole sample, while panels (b)–(d) refer to specific age groups (18–29; 30–49; 50–64). The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

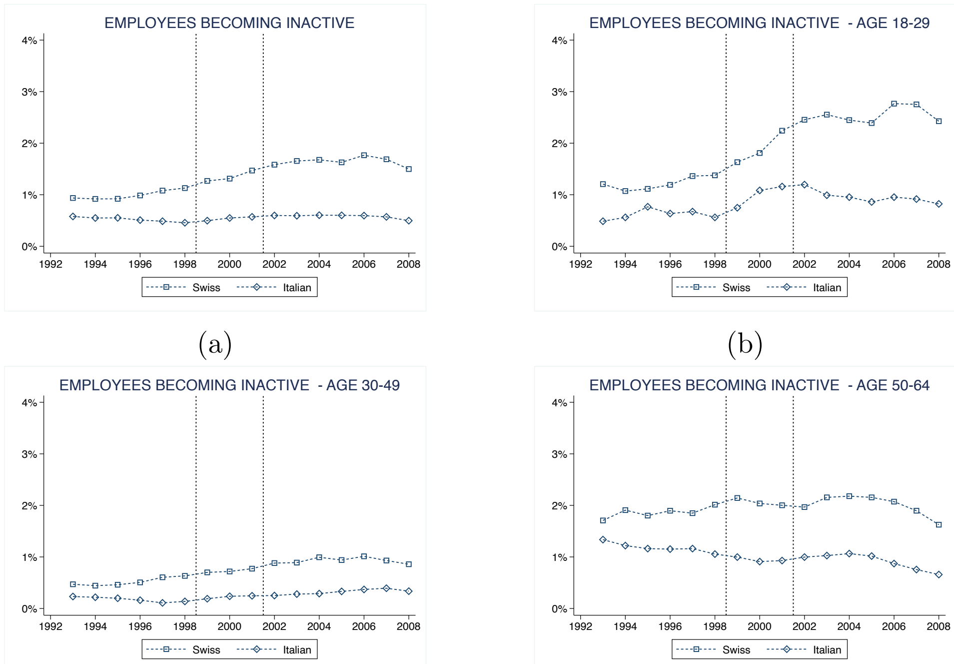
Figure 2.6.1 shows the evolution of the number of Swiss and Italian employees in Ticino (irrespective of treatment status). After a decreasing trend until 1999, the number of Italian employees increased sharply, while for Swiss employees the initial upward trend stops and becomes flat in 2000 (panel a). The breakdown by age group shows that not only the number of young Italian employees aged 18–29 exhibits sizeable growth (panel b), but there is an even steeper increase in the number of Italians aged 30–49, while the number of Swiss employees rises before 1999 and then flattens out (panel c). Finally, there are no visible effects among older employees (panel d). All in all, Figure 2.6.1 suggests that the policy change may have contributed to an expansion of the labor market. While the total number of employees was already slightly increasing before 1999 as the result of the rising number of Swiss employees, a subsequent steeper growth took place, driven by Italian immigrants.

(c) (d)

Figure 2.6.2: Employees' (log) real wages by nationality and age group

Notes: This figure shows the evolution over time (1992-2008) of the average (log) real monthly wage of male employees in private sector firms with at least two employees. Each panel compares the evolution of wages for Swiss and Italian employees. Panel (a) refers to the whole sample, while panels (b)–(d) refer to specific age groups (18–29; 30–49; 50–64). The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

Next, Figure 2.6.2 focuses on the average real wages of Swiss and Italian employees by age group. In general, we observe a small overall increase in the average wages of Swiss employees after 2002 (panel a). However, for young natives (panel b) the initial decreasing trend becomes steeper after 1999. We observe the opposite pattern for middle-aged Swiss employees, with a clear increase in their wages after 1999 (panel c),[27] while there is no relevant change for older employees (panel d).



(a) (b) (c) (d)

Figure 2.6.3: Share of employees becoming inactive by nationality and age group

Notes: This figure shows the evolution over time (1993-2008) of the average share of male employees becoming inactive (i.e., inactive, long-term unemployed, or early retired) in private sector firms with at least two employees, holding the denominator fixed in 1998. Each panel compares the evolution of transitions to inactivity between Swiss and Italian employees. Panel (a) refers to the whole sample, while panels (b)–(d) refer to specific age groups (18–29; 30–49; 50–64). The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

Finally, Figure 2.6.3 reports the evolution of the average shares of Swiss employees in different age groups who leave the labor force, holding the denominator fixed in 1998. Consistently with our micro empirical results, the share of Swiss employees who become inactive exhibits a growing tendency after 1999 (panel a). This pattern is driven by a sizeable increase for young employees (panel b), while we do not observe any relevant

[27]The decrease in middle-aged Swiss employees' average wages during the second half of the 1990s, instead, is likely driven by the reintegration in the labor market of previously unemployed individuals during the 1991-94 Swiss recession.

change for their middle-aged counterparts (panel c). On the contrary, the average share of older people becoming inactive decreases more sharply after the reform (panel d), mirroring a likely reduction in the share of early retirees.

2.6.2 Theory-based interpretation

According to a standard model of demand and supply in a competitive labor market, a massive inflow of qualified immigrant workers would lead to a decrease in wages and employment opportunities for same-language natives with comparable certifications.

However, a growing strand of literature has proposed an alternative class of models that predicts a positive effect of immigration on labor market outcomes (Pissarides, 2000). In this setting, the inflow of high-skilled immigrants leads to an expansion of the labor market, thanks to the attraction of new previously scarce skills and to the opening of new job positions. This leads not only to a positive effect on employment, but also to an increase in wages if the production function exhibits increasing returns to education, especially when combined with experience, because of the positive externalities induced by qualified workers.

Our empirical results can be rationalized in light of both types of models. First, differently from the expectations based on a standard competitive model, we show that the recognition of EU diplomas introduced by the AFMP did lead to a massive inflow of young qualified Italian workers in Ticino, but had an almost negligible aggregate effect on native employees' outcomes. As reported in Figure 2.3.1, this is likely the result of a labor market expansion, especially in sectors such as IT. Yet, we document that this overall result masks an important heterogeneity across age (i.e., experience) groups. While Swiss incumbent experienced employees enjoyed a wage gain and a decrease in the likelihood of becoming inactive, the opposite happened for young inexperienced citizens entering the labor market after the reform.

These results can be interpreted in the context of a model in which native workers are heterogeneous and exhibit different patterns of complementarity and substitutability with immigrants (see, e.g., Borjas, 2003; Ottaviano and Peri, 2012; Gentili and Mazzonna, 2017). In this framework, the AFMP should negatively affect the wage (i.e., marginal product of labor) and probability of employment of native workers who are substitutable with competing immigrants. On the contrary, native workers with characteristics that are complementary to those of immigrants should experience a wage gain and a higher likelihood of being employed.

In our case, the policy led to a disproportionate increase in the number of young qualified immigrant workers sharing the same linguistic background with natives. These immigrants, however, lack experience of the local labor market (as in, e.g., Chiswick, 1978). Young Italian immigrants are therefore likely to substitute young Swiss workers entering the labor market after the recognition of EU qualifications, while they are complementary to experienced incumbents.

The concentration of wage gains among high-ability incumbents is consistent with the fact that experienced workers with high ability are not only complementary to immigrants, but are also likely to exhibit a higher degree of complementarity with available physical capital (Lewis and Peri, 2015).

2.7 Conclusions

This paper contributes to the extensive economic literature and policy debate on the labor market effects of immigration by investigating the consequences of an inflow of qualified foreign workers who hold fully equivalent certifications with respect to native employees and do not experience any linguistic barrier.

To this aim, we leverage the natural experiment represented by the opening of the Swiss labor market to workers from EU countries by recognizing their qualifications. Our analysis focuses on Ticino, the only Italian-speaking Swiss canton, where Italian (cross-border) workers represent a high share of the labor force. Using a difference-in-differences empirical strategy to compare over time economic sectors differently affected by the recognition of EU diplomas, we first estimate a large increase in the share of young Italian workers in firms after the policy.

Considering native employees' labor market outcomes, we show that the almost negligible average effect of the AFMP masks a substantial heterogeneity across age groups. While we provide evidence of a wage gain for middle-aged (30–49) employees, the impact of the policy turns out to be negative for younger (18–29) employees. More specifically, the former effect is driven by high-ability employees and is more likely to materialize when moving to a different firm, whereas the latter effect is explained by a decrease in the entry wages earned by young employees entering the labor market after the policy change. We show that part of this negative effect can be explained by the growing share of (college educated) Swiss residents aged 25–29 moving to other cantons, which changes the skill composition of the young new employees entering the local labor market.

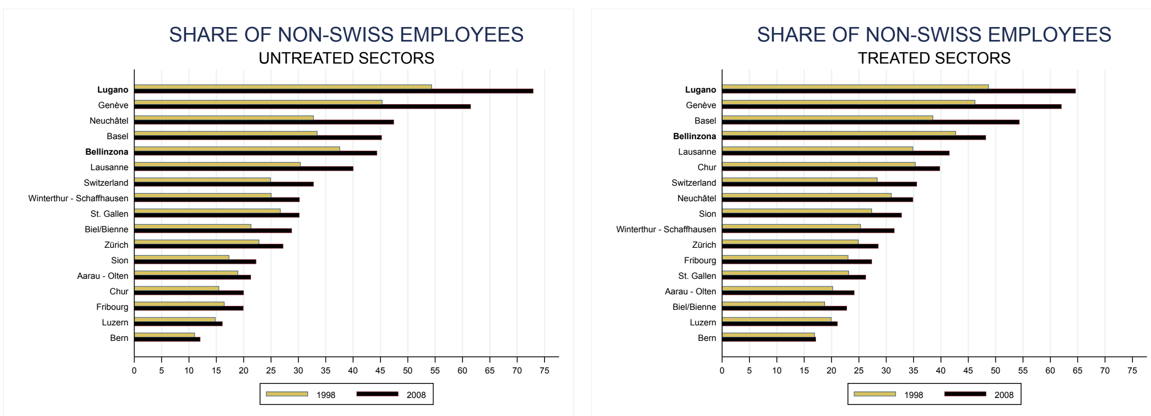
According to our estimates, the reform is also associated with an increase in the probability of inactivity for young new entrants, while middle-aged and older incumbents have become less likely to experience long-term unemployment or, more generally, to leave the labor force.

Interpreting age as a proxy for the amount of labor market experience of the individual, our findings suggest that young Italian immigrants are complementary to incumbent Swiss employees, but are close substitutes for native new entrants with equivalent qualifications and the same linguistic background. This interpretation is strengthened by the absence of any negative effect for Italian employees already active in Switzerland before the policy change.

Our results also open the path for future lines of research. First, while our analysis focuses on the impact of the policy on individual labor market outcomes, more attention may be devoted to study firms' choices and outcomes when the pool of available workers enlarges and there are different patterns of complementarity and substitutability between natives and immigrants. Second, the disparities in the effects between native workers belonging to different generations, with adverse consequences borne by young newcomers in the labor market and gains enjoyed by incumbents, ask for a deeper understanding of social welfare implications of immigration policies and for an evaluation of the most adequate interventions to compensate potential arising inequalities.

Appendix B

B.1 Additional Figures



(a) (b)

Figure B.1.1: Non-Swiss employees by labor market region

Notes: This figure represents the share of non-Swiss employees in private sector firms with at least two employees in the sixteen Swiss large labor market regions (Swiss Federal Statistical Office, 2000) in 1998 and 2008. Our dataset covers the regions of Lugano (which accounts for almost 80% of private sector firms in the canton of Ticino in 2008) and Bellinzona. Panels (a) and (b) refer to untreated and treated sectors, respectively.
Source: Our calculations on *Business Census* data.

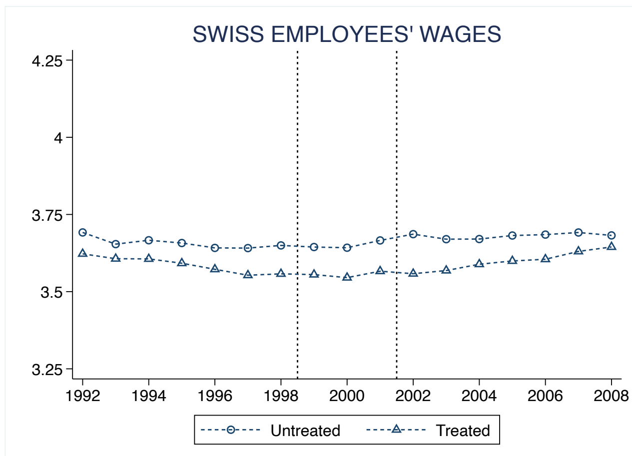
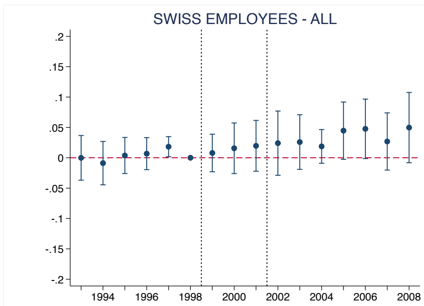
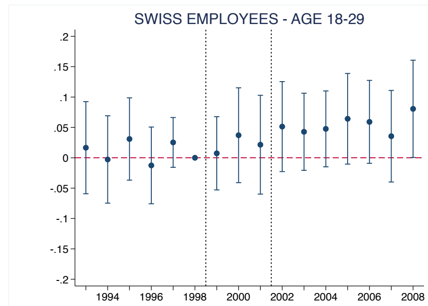


Figure B.1.2: Swiss employees' average (log) real monthly wages by

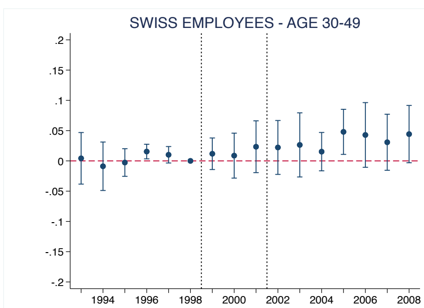
Notes: This descriptive figure shows the evolution over time (1992–2008) of the average value of the (log) real monthly wage earned by Swiss male employees in private sector firms with at least two employees, comparing treated and untreated sectors. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



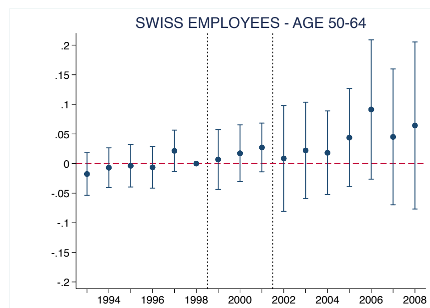
(a)



(b)



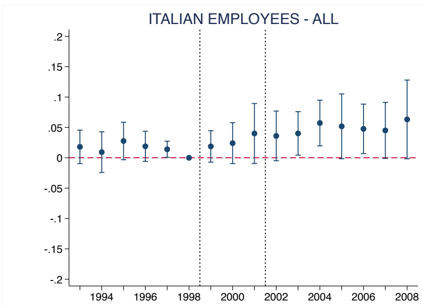
(c)



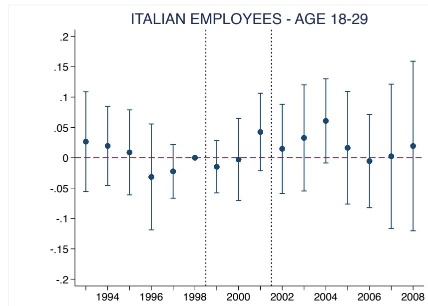
(d)

Figure B.1.3: Incumbent Swiss employees' (log) real monthly wages – Dynamic DiD model

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2), when treatment status and age are fixed in 1998 ("frozen" model). Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



(a)



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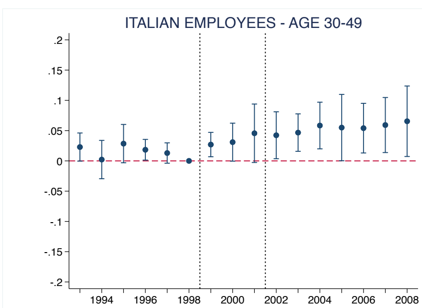
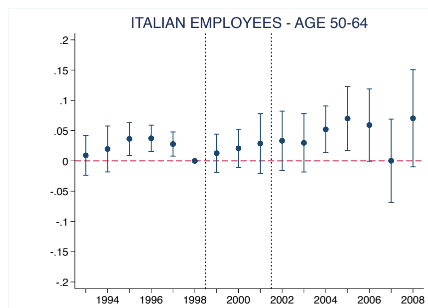


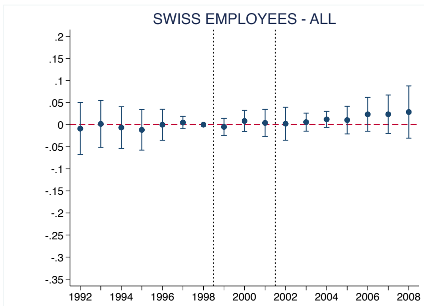
(c)



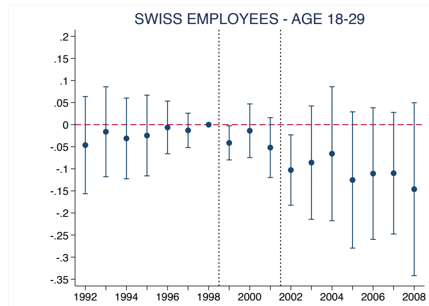
(d)

Figure B.1.4: Incumbent Italian employees' (log) real monthly wages – Dynamic DiD model

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2), when treatment status and age are fixed in 1998 ("frozen" model). Panel (a) refers to the full sample of Italian male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



(a)



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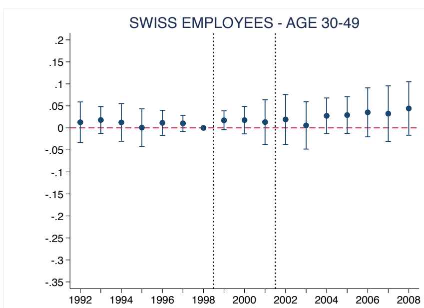

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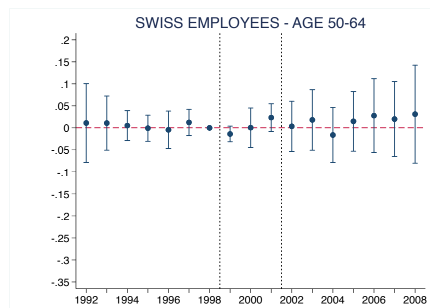
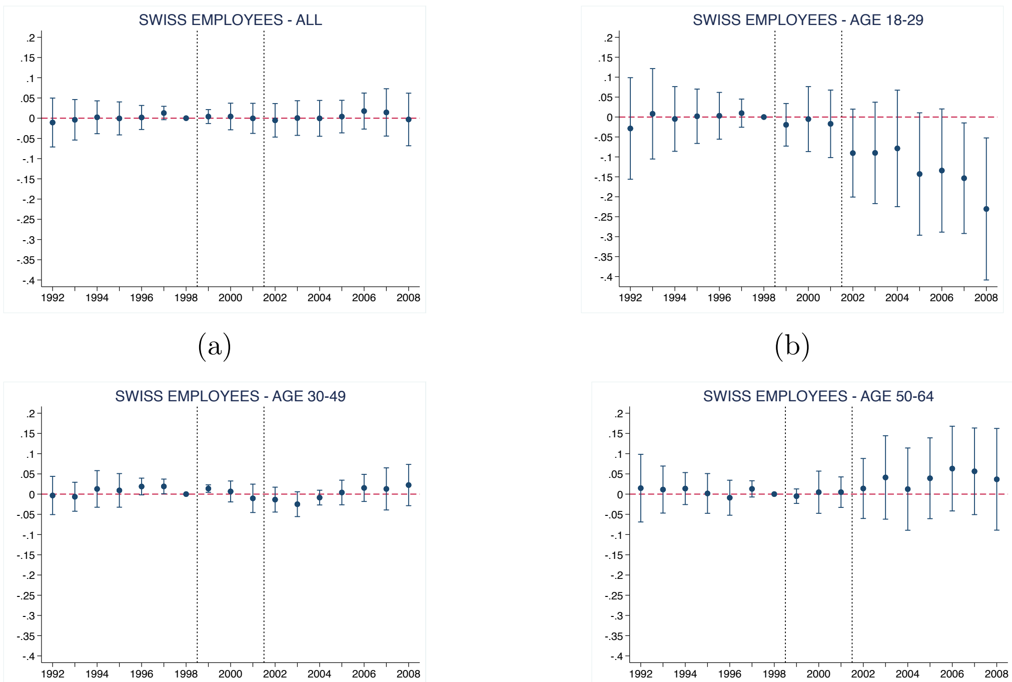


(d)

Figure B.1.5: Swiss employees' (log) real monthly wages – Dynamic DiD for employees who did not change treatment status

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2) excluding employees who change treatment status. Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



(a) (b)

(c) (d)

Figure B.1.6: Swiss employees' (log) real monthly wages – Dynamic DiD for employees who did not change firm

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2) excluding employees who changed firm. Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

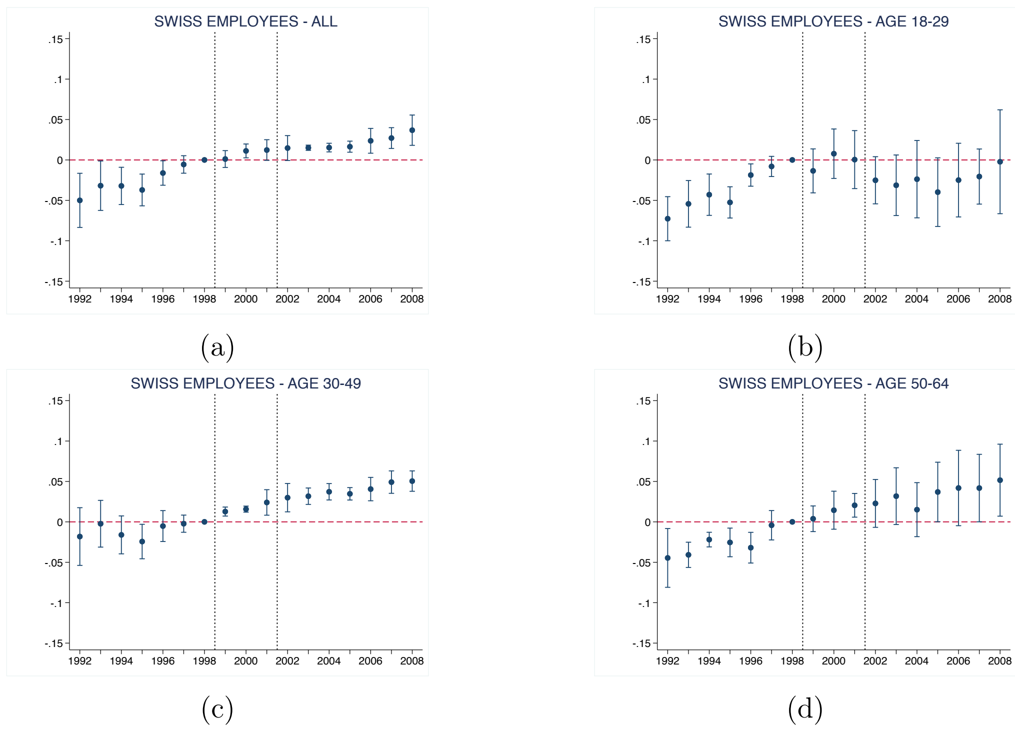
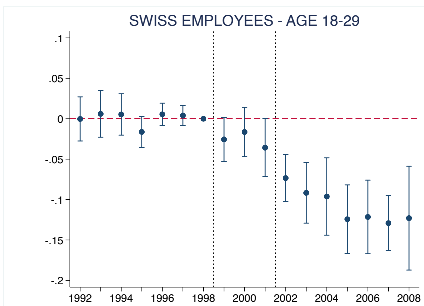
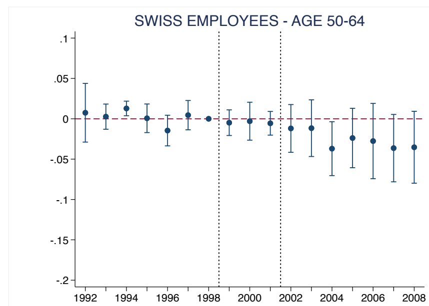


Figure B.1.7: Swiss employees' (log) real monthly wage – Dynamic DiD with continuous treatment

Notes: This figure shows the estimates from an alternative version of the dynamic difference-in-differences model (2.2), in which the dummy variable for each year is interacted with the continuous share of treated occupations in each sector. Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



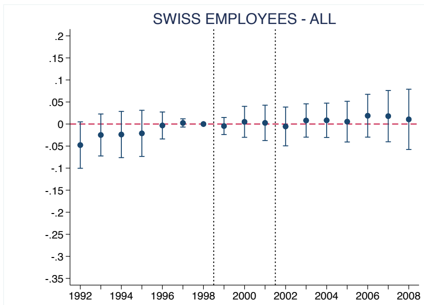
(a)



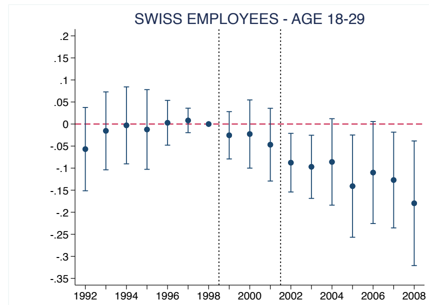
(b)

Figure B.1.8: Swiss employees' (log) real monthly wages – Dynamic DiD model with continuous treatment – Pre-trends correction

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2) where the outcome variable is the real monthly wage net of a linear pre-trend that varies with the intensity of the treatment, which has been estimated using only the pre-policy period (1992–1998). Panel (a) and (b) refer to the Swiss male employees in private sector firms with at least two employees aged, respectively, 18–29 and 50–64. Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



(a)



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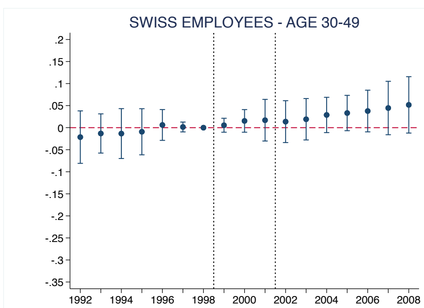

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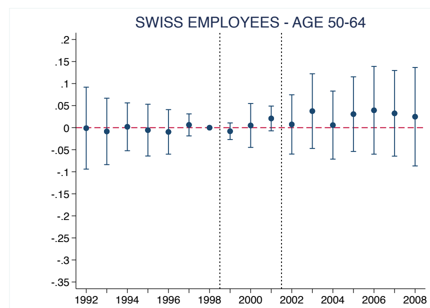
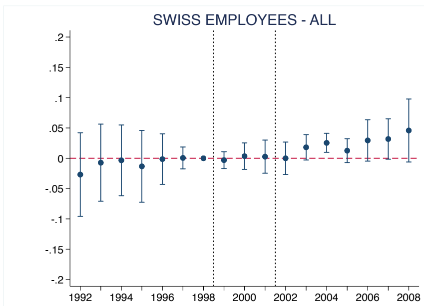


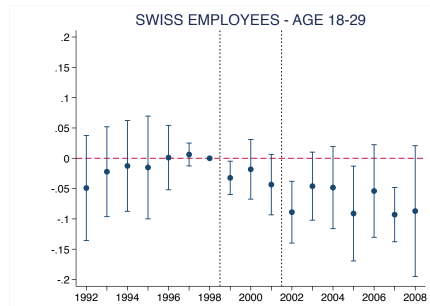
(d)

Figure B.1.9: Swiss employees' (log) real monthly wages – Dynamic DiD model with firm fixed effects

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2). Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include firm (instead of sector), district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



(a)



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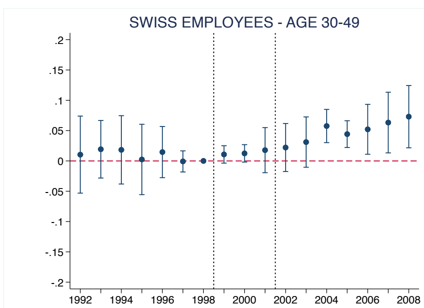

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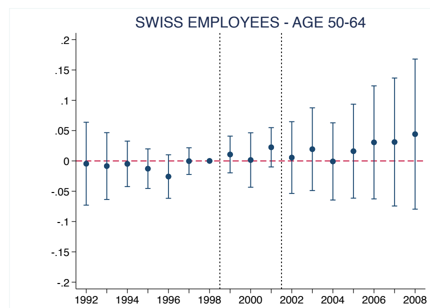
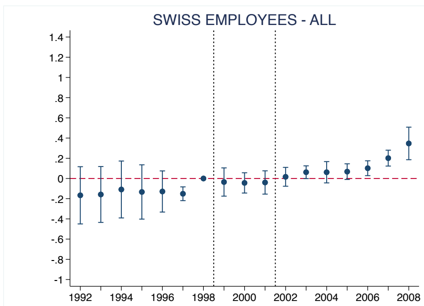


(d)

Figure B.1.10: Swiss employees' (log) real monthly earnings – Dynamic DiD model

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2), when the outcome variable is the logarithm of real total monthly earnings. Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.



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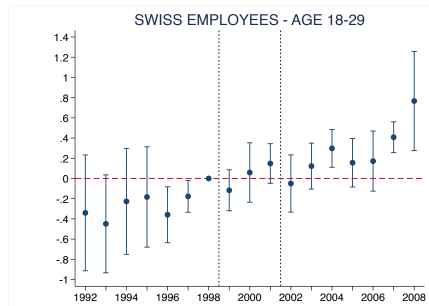

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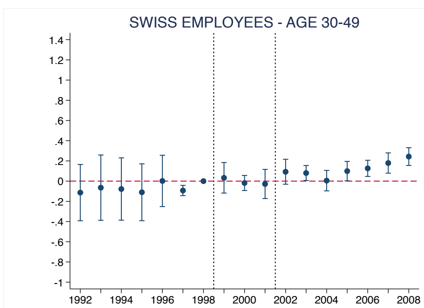

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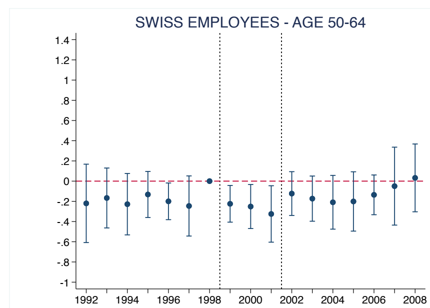


(d)

Figure B.1.11: Swiss employees' months worked – Dynamic DiD model

Notes: This figure shows the estimates from the dynamic difference-in-differences model (2.2), when the outcome variable is the number of months worked every year by each employee. Panel (a) refers to the full sample of Swiss male employees in private sector firms with at least two employees, while panels (b)–(d) focus on different age groups (18–29; 30–49; 50–64). Each graph shows the estimates of the coefficients β_k (k = 1992,..., 1997, 1999, ..., 2008) with the corresponding confidence intervals at the 5% significance level. The last year before the Agreement on the Free Movement of Persons was signed (i.e., 1998) is the omitted year. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The first vertical dashed line (between 1998 and 1999) indicates the beginning of the transitional phase following the announcement of the AFMP, while the second line (between 2001 and 2002) identifies the period characterized by its full enactment.

B.2 Additional Tables

Table B.2.1: Treated and untreated sectors

	Share treated occupations	Share of Italian employees			
		1992	1998	2002	2008
Panel A: Treated Sectors					
Information Technology and Auxiliary to Trade	78.05%	33.42%	32.00%	35.40%	51.57%
Legal Assistance	64.64%	8.63%	8.97%	9.52%	13.01%
Hotels, restaurants	59.90%	30.40%	24.95%	33.22%	41.30%
Art, Theater, Entertainment	50.33%	28.65%	26.29%	32.21%	53.73%
Chemical Industry	48.01%	46.41%	45.31%	54.14%	62.35%
Communication and Transports	43.61%	42.70%	38.91%	40.82%	40.76%
Construction, Engineering and Architecture	36.19%	55.72%	48.76%	51.16%	52.85%
Panel B: Untreated Sectors					
Wholesale Trade	23.94%	32.87%	40.69%	43.71%	48.36%
Textile Industry	22.02%	68.20%	64.64%	63.47%	74.47%
Jewelry Industry	21.43%	47.98%	42.63%	42.27%	50.34%
Minerary Industry	20.15%	55.53%	48.95%	52.34%	58.54%
Metallurgic Industry	19.67%	54.17%	47.92%	52.82%	56.63%
Graphic Industry	18.92%	32.44%	31.32%	26.00%	33.33%
Retail Trade	8.64%	45.99%	41.36%	42.27%	50.39%
Domestic Services	5.74%	39.13%	43.21%	39.53%	39.32%
Wood Industry	1.26%	47.32%	36.61%	35.06%	32.83%
Wine and Drinks Industry	0.00%	49.09%	58.06%	55.56%	35.71%

Notes: This table reports the share of employees in treated occupations in each sector in Ticino according to data from the Swiss Labor Force Survey over the period 1996–2008 (first column) and the share of male employees of Italian nationality working in private sector firms with at least two employees in Ticino in 1992, 1998, 2002, and 2008. Panel A refers to treated economic sectors, namely those which were affected by the mutual recognition of diplomas and qualifications implied by the Agreement on the Free Movement of Persons between Switzerland and the European Union (2002), while Panel B refers to untreated sectors. *Source:* Our calculations on data from *SLFS* and *Istituto delle Assicurazioni Sociali*.

Table B.2.2: Shares of treated occupations over time by sector

	Pre (1996–2002)	Post (2002–2008)
Panel A: Treated Sectors		
Information Technology and Auxiliary to Trade	74.96%	76.70%
Legal Assistance	70.89%	64.95%
Hotels, restaurants	56.66%	57.76%
Art, Theater, Entertainment	48.87%	39.12%
Chemical Industry	43.20%	47.21%
Communication and Transports	36.85%	45.61%
Construction, Engineering and Architecture	30.13%	32.45%
Panel B: Untreated Sectors		
Wholesale Trade	38.49%	32.75%
Metallurgic Industry	33.10%	34.44%
Domestic Services	22.70%	24.70%
Textile Industry	22.61%	8.64%
Minerary Industry	21.52%	20.05%
Wine and Drinks Industry	21.35%	13.04%
Retail Trade	20.72%	23.34%
Jewelry Industry	14.45%	17.22%
Graphic Industry	14.42%	15.72%
Wood Industry	5.59%	4.36%

Notes: This table reports the shares of employees in treated occupations in each sector in Switzerland, distinguishing the years before (1996–2002) and after (2002–2008) the enactment of the Agreement on the Free Movement of Persons between Switzerland and the European Union (2002). Panel A refers to treated economic sectors, namely those which were more affected in Ticino by the mutual recognition of diplomas and qualifications implied by the Agreement on the Free Movement of Persons, while Panel B refers to untreated sectors. These shares might slightly differ from those reported in Column (1) of Appendix Table B.2.1 because in this case they are computed using data for all Switzerland and not only for the canton of Ticino. This is due to the limitations of the Swiss Labor Force Survey before 2002, as the low number of observations and the non-representativeness of data at canton level would not allow to obtain reliable estimates for Ticino only in the pre-period.

Table B.2.3: Descriptive statistics (1992-2008)

	All			Age 18-29			Age 30-49			Age 50-64		
	Pre 1998	1999-2001	Post 2002	Pre 1998	1999-2001	Post 2002	Pre 1998	1999-2001	Post 2002	Pre 1998	1999-2001	Post 2002
PANEL A: TREATED SECTORS												
Swiss Employees												
Share	50.36%	53.31%	45.29%	63.41%	65.59%	49.58%	46.34%	50.31%	42.86%	44.10%	47.41%	47.23%
(Log) Real Monthly Wage	3.58	3.56	3.60	3.22	3.09	3.02	3.76	3.74	3.80	3.78	3.75	3.79
	(0.91)	(1.01)	(1.02)	(0.82)	(0.97)	(0.97)	(0.85)	(0.92)	(0.91)	(0.98)	(1.06)	(1.05)
(Log) Entry Wage at New Job	3.42	3.43	3.38	3.18	3.17	3.01	3.60	3.59	3.62	3.58	3.56	3.47
	(0.88)	(0.92)	(0.99)	(0.79)	(0.86)	(0.92)	(0.86)	(0.89)	(0.92)	(1.05)	(1.06)	(1.17)
Transitions to Inactivity	1.55%	1.66%	2.02%	1.99%	2.95%	4.55%	0.81%	0.77%	1.00%	2.75%	2.32%	2.03%
Italian Employees												
Share	41.22%	38.28%	45.50%	28.28%	26.34%	39.55%	43.29%	39.93%	47.82%	52.19%	47.25%	45.82%
(Log) Real Monthly Wage	3.64	3.65	3.58	3.39	3.28	3.19	3.71	3.73	3.67	3.66	3.70	3.71
	(0.61)	(0.71)	(0.78)	(0.66)	(0.76)	(0.78)	(0.55)	(0.66)	(0.75)	(0.66)	(0.73)	(0.76)
(Log) Entry Wage at New Job	3.54	3.58	3.52	3.27	3.29	3.26	3.64	3.65	3.60	3.59	3.63	3.58
	(0.66)	(0.71)	(0.72)	(0.73)	(0.70)	(0.70)	(0.58)	(0.65)	(0.70)	(0.69)	(0.78)	(0.79)
Transitions to Inactivity	0.78%	0.75%	0.64%	0.85%	1.60%	0.83%	0.26%	0.30%	0.37%	1.85%	1.23%	1.30%
PANEL B: UNTREATED SECTORS												
Swiss Employees												
Share Swiss	43.72%	45.47%	41.01%	56.41%	60.48%	50.92%	38.86%	41.35%	38.12%	38.69%	39.84%	38.78%
(Log) Real Monthly Wage	3.66	3.65	3.68	3.28	3.25	3.19	3.85	3.81	3.84	3.90	3.87	3.89
	(0.74)	(0.77)	(0.79)	(0.71)	(0.74)	(0.78)	(0.62)	(0.65)	(0.67)	(0.78)	(0.83)	(0.82)
(Log) Entry Wage at New Job	3.44	3.44	3.45	3.28	3.29	3.22	3.63	3.59	3.63	3.56	3.40	3.57
	(0.70)	(0.72)	(0.80)	(0.64)	(0.65)	(0.70)	(0.67)	(0.72)	(0.78)	(0.87)	(0.86)	(0.94)
Transitions to Inactivity	1.00%	1.21%	1.41%	1.15%	1.44%	2.44%	0.54%	0.78%	0.75%	1.86%	1.91%	1.89%
Italian Employees												
Share	49.17%	47.35%	51.38%	36.71%	31.21%	38.15%	52.64%	50.41%	54.35%	57.28%	56.61%	56.52%
(Log) Real Monthly Wage	3.64	3.66	3.64	3.40	3.38	3.33	3.71	3.71	3.70	3.70	3.73	3.71
	(0.48)	(0.50)	(0.56)	(0.52)	(0.57)	(0.60)	(0.41)	(0.43)	(0.49)	(0.53)	(0.55)	(0.61)
(Log) Entry Wage at New Job	3.52	3.60	3.55	3.31	3.36	3.34	3.59	3.69	3.62	3.61	3.58	3.61
	(0.54)	(0.53)	(0.54)	(0.62)	(0.57)	(0.56)	(0.46)	(0.47)	(0.49)	(0.56)	(0.58)	(0.64)
Transitions to Inactivity	0.43%	0.42%	0.24%	0.20%	0.58%	0.37%	0.16%	0.19%	0.08%	1.25%	0.82%	0.55%

Notes: This table shows descriptive statistics for our sample of private sector male employees in firms with at least two employees. Panels A and B focus on treated and untreated sectors, respectively, and compare for every single age group three periods (before 1998, between 1999 and 2001, after 2002). Standard deviations in parentheses.

Source: Our calculations on data from Istituto delle Assicurazioni Sociali.

Table B.2.4: Incumbent Italian employees' labor market outcomes (1992-2008)

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
Panel A: (Log) real monthly wages				
treated × transition	0.015	0.010	0.022	0.001
	(0.024)	(0.040)	(0.022)	(0.024)
treated × post2002	0.035	0.024	0.042	0.023
	(0.029)	(0.055)	(0.027)	(0.031)
N	134449	16667	83166	34615
Mean in 1998 (T)	3.64	3.31	3.71	3.67
Mean in 1998 (U)	3.66	3.38	3.71	3.72
Panel B: Probability of inactivity				
treated × transition	-0.005	-0.013*	-0.003	-0.003
	(0.003)	(0.007)	(0.002)	(0.006)
treated × post2002	-0.001	-0.010	-0.000	0.011
	(0.003)	(0.007)	(0.001)	(0.010)
N	132947	16367	81872	34707
Mean in 1998 (T)	0.78%	1.46%	0.10%	1.91%
Mean in 1998 (U)	0.41%	0.00%	0.13%	1.23%

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) when treatment status and age are fixed in 1998 ("frozen" model). Column (1) reports the estimates for the full sample of Italian male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). Panel A refers to wages, while panel B to the probability of becoming inactive. All models include sector, district, year, and (only for wages) individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The last two rows of Panel A display the average (log) real monthly wages of Italian employees by age group in 1998 in treated (T) and untreated (U) sectors, respectively. The last two rows of Panel B display the average shares of Italian employees becoming inactive in Ticino. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table B.2.5: Incumbent Swiss employees' (log) real monthly wages by ability (1992-2008)

	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)
treated × transition	-0.005	0.001	0.013
	(0.042)	(0.012)	(0.030)
treated × transition × high	-0.004	0.080*	0.045
	(0.046)	(0.038)	(0.063)
treated × post2002	-0.023	0.033	0.093
	(0.037)	(0.040)	(0.072)
treated × post2002 × high	0.132**	0.043	-0.075
	(0.054)	(0.032)	(0.061)
N	33510	76341	27530
Mean in 1998 (T)	3.31	3.78	3.83
Mean in 1998 (U)	3.38	3.85	3.92

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) when treatment status and age are fixed in 1998 ("frozen" model). In these models we control for high ability by considering the top tercile of the predicted distribution of individual fixed effects (between 1992 and 1998) for Swiss employees active in 1998. Columns (1)-(3) report the estimates for Swiss male employees in private sector firms with at least two employees, distinguishing between different age groups (18–29; 30–49; 50–64), fixed in 1998. All models include sector, district, and year fixed effects, plus a linear and a quadratic age term and a dummy for high ability. Robust standard errors are two-way clustered at sector and year level. The last two rows display the average (log) real monthly wages of Swiss employees by age group in 1998 in treated (T) and untreated (U) sectors, respectively.
Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table B.2.6: Incumbent Swiss employees' (log) real monthly wages (1992-2008)

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
Panel A: At same firm as 1998				
treated × transition	0.001	-0.004	0.012	-0.008
	(0.024)	(0.039)	(0.022)	(0.024)
treated × post2002	0.020	0.027	0.016	0.033
	(0.041)	(0.065)	(0.033)	(0.059)
N	82448	15292	45659	21497
Panel B: Changing employer				
treated × transition	0.022	0.010	0.019	0.116***
	(0.018)	(0.030)	(0.025)	(0.031)
treated × post2002	0.053***	0.041	0.073***	0.101**
	(0.017)	(0.030)	(0.024)	(0.039)
N	65719	23781	34897	7041
Mean in 1998 (T)	3.56	3.20	3.70	3.75
Mean in 1998 (U)	3.65	3.27	3.82	3.88

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) when treatment status and age are fixed in 1998 ("frozen" model). Column (1) reports the estimates for the full sample of Swiss male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). Panel A refers to the subsample of employees who always remained at the same firm where they were active in 1998, while panel B refers to the subsample of employees who changed employer over time. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The last two rows display the average (log) real monthly wages of Swiss employees by age group in 1998 in treated (T) and untreated (U) sectors, respectively.
Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table B.2.7: Employees' real monthly wages by years of experience (1992-2008)

	Swiss			Italian		
	All	1-4 years	5+ years	All	1-4 years	5+ years
	(1)	(2)	(3)	(4)	(5)	(6)
treated × transition	0.001	-0.046*	0.013	0.009	-0.020	0.022
	(0.013)	(0.022)	(0.014)	(0.016)	(0.026)	(0.013)
treated × post2002	-0.007	-0.025	0.008*	0.015	0.013*	0.014
	(0.020)	(0.027)	(0.004)	(0.010)	(0.007)	(0.010)
N	194162	87726	102374	182648	84017	94377
Mean in 1998 (T)	3.47	3.22	3.77	3.61	3.49	3.72
Mean in 1998 (U)	3.56	3.32	3.79	3.62	3.47	3.69

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) when considering acquired experience rather than age. Columns (1)-(3) refer to Swiss male employees in private sector firms with at least two employees, while Columns (4)-(6) refer to Italian male employees. All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic term for experience. Robust standard errors are two-way clustered at sector and year level. The last two rows display the average (log) real monthly wages of Swiss and Italian employees by experience group in 1998 in treated (T) and untreated (U) sectors, respectively.
Significance levels: *** p $<$ 0.01; ** 0.01 $\leq$ p $<$ 0.05; * 0.05 $\leq$ p $<$ 0.10.

Table B.2.8: Swiss employees' probability of changing labor market status (1992-2008)

	Age 18-29	Age 30-39	Age 40-49	Age 50-57	Age 58-64
	(1)	(2)	(3)	(4)	(5)
Panel A: Employee in Private Sector					
treated × transition	-0.002	0.001	-0.001	0.004	0.042**
	(0.011)	(0.007)	(0.007)	(0.007)	(0.020)
treated × post2002	-0.023***	0.008**	0.010**	0.013***	0.067***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.012)
Mean in 1998 (T)	83.85%	90.47%	90.12%	90.26%	77.93%
Mean in 1998 (U)	89.38%	92.20%	94.62%	94.55%	78.21%
Panel B: Inactive					
treated × transition	0.002	-0.001	-0.004***	-0.004*	-0.006
	(0.003)	(0.001)	(0.001)	(0.002)	(0.006)
treated × post2002	0.008***	-0.001	-0.003***	-0.006***	-0.019***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)
Mean in 1998 (T)	2.25%	0.66%	1.30%	0.76%	4.73%
Mean in 1998 (U)	1.00%	0.54%	0.70%	0.72%	4.36%
Panel C: Exit					
treated × transition	-0.001	-0.001	0.002	-0.001	-0.035**
	(0.009)	(0.007)	(0.007)	(0.006)	(0.016)
treated × post2002	0.015***	-0.004	-0.004	-0.005	-0.046***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.011)
Mean in 1998 (T)	8.45%	5.56%	5.50%	6.49%	15.76%
Mean in 1998 (U)	6.03%	5.48%	3.59%	3.59%	16.95%
Panel D: To Public Sector					
treated × transition	0.001	0.001	0.003	0.002	-0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
treated × post2002	-0.000	-0.002	-0.003	-0.002	-0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Mean in 1998 (T)	5.45%	3.31%	3.08%	2.48%	1.58%
Mean in 1998 (U)	3.60%	1.79%	1.10%	1.15%	0.48%

Notes: This table shows the estimates of the marginal effects of the difference-in-differences coefficients of the multinomial logit model (2.4) (see Appendix B.3) for the probability of changing labor market status for Swiss male employees in private sector firms with at least two employees. According to this model specification, a private sector employee can remain employed, become inactive (i.e., out of the labor force or long-term unemployed in Ticino), leave the dataset, or move to the public sector. The model includes sector, district, and year fixed effects. Robust standard errors are two-way clustered at sector and year level. The last two rows of each panel display the shares of employees remaining employed (Panel A), becoming inactive (Panel B), leaving the dataset (Panel C), or moving to the public sector (Panel D) in 1998 by age group in treated (T) and untreated (U) sectors, respectively.
Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$. $N = 238,131$ observations.

Table B.2.9: Swiss employees' (log) real monthly wages upon changing firm (1992-2008)

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
treated × transition	0.036	0.009	0.083	0.105
	(0.041)	(0.037)	(0.050)	(0.063)
treated × post2002	0.069	0.011	0.097**	0.025
	(0.049)	(0.057)	(0.045)	(0.100)
N	11874	4322	5123	941
Mean in 1998 (T)	3.48	3.21	3.62	3.77
Mean in 1998 (U)	3.48	3.36	3.65	3.46

Notes: This table shows the estimates of the difference-in-differences coefficients of model (2.3) for the wages earned by Swiss employees in the first year after moving to a different (private sector) firm. Column (1) reports the estimates for the full sample of Swiss male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). All models include sector, district, year, and individual fixed effects, plus a linear and a quadratic age term. Robust standard errors are two-way clustered at sector and year level. The last two rows display the value of the average (log) real monthly wages earned by Swiss employees upon arrival at a new firm by age group in 1998 in treated (T) and untreated (U) sectors, respectively.
Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table B.2.10: Swiss employees' labor market outcomes (1992-2008) - Triple difference-in-differences model

	All	Age 18-29	Age 30-49	Age 50-64
	(1)	(2)	(3)	(4)
Panel A: (Log) real monthly wages				
treated × transition	-0.017	-0.028	-0.028	0.019
	(0.019)	(0.040)	(0.025)	(0.019)
treated × transition × border	0.040***	0.005	0.063***	-0.012
	(0.010)	(0.031)	(0.018)	(0.048)
treated × post2002	0.002	-0.043	-0.010	0.020
	(0.025)	(0.052)	(0.029)	(0.036)
treated × post2002 × border	0.021	-0.045	0.072***	-0.023
	(0.013)	(0.053)	(0.023)	(0.057)
N	243209	68542	122407	47705
Mean in 1998 (T)	3.56	3.20	3.70	3.75
Mean in 1998 (U)	3.65	3.27	3.82	3.88
Panel B: Probability of inactivity				
treated × transition	-0.000	0.007*	-0.004***	-0.002
	(0.001)	(0.004)	(0.001)	(0.004)
treated × transition × border	-0.003**	-0.007	0.002	-0.004
	(0.001)	(0.005)	(0.001)	(0.003)
treated × post2002	-0.001	0.005	-0.001	-0.007
	(0.002)	(0.005)	(0.002)	(0.005)
treated × post2002 × border	0.003***	0.008***	0.002	0.002
	(0.001)	(0.002)	(0.001)	(0.005)
N	227814	61428	119710	46676
Mean in 1998 (T)	1.73%	2.61%	1.00%	2.46%
Mean in 1998 (U)	1.11%	1.10%	0.64%	2.29%

Notes: This table shows the estimates for an alternative version of model (2.3), in which we consider also the role of distance from the border using a triple difference-in-differences estimator. Border municipalities are those whose distance from the nearest border crossing office is at most 5 km. Column (1) reports the estimates for the full sample of Swiss male employees in private sector firms with at least two employees, while Columns (2)-(4) focus on different age groups (18–29; 30–49; 50–64). Panel A refers to wages, while panel B to the probability of becoming inactive All models include sector, district, year, and (only for wages) individual fixed effects, plus a linear and a quadratic age term and all the further interaction terms. Robust standard errors are two-way clustered at sector and year level. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

B.3 The multinomial logit model

In order to study the impact of the policy on employees' likelihood of changing labor market status, we estimate the following multinomial logit model for the probability of staying employed, becoming inactive, leaving the dataset, or moving to the public sector:

$$\begin{aligned} S_{iast} = \alpha + \sum_{a=0}^{4} \eta_{1,a} treated_{it} \times transition_t \times age_a + \\ \sum_{a=0}^{4} \eta_{2,a} treated_{it} \times post2002_t \times age_a + \chi_d + \lambda_s + \mu_t + \epsilon_{iast} \end{aligned} \tag{2.4}$$

The outcome variable S_{iast} is the labor market status in year $t+1$ (employed, inactive, exit) of employee i in age group a (18–29; 30–39; 40–49; 50–57; 58+) and economic sector s in year t. This specification is similar to model (2.3), except for the exclusion of individual fixed effects. Hence, it only includes sector (λ_s), year (μ_t), and district (χ_d) fixed effects. Moreover, the relatively low number of annual transitions to inactivity or exit in every single age group prevents us from splitting the sample by age. We, therefore, explore the potential heterogeneity across this dimension by further interacting $treated_{it} \times transition_t$ and $treated_{it} \times post2002_t$ with dummy variables for age groups.

We are interested in the age group-specific coefficients $\eta_{1,a}$ and $\eta_{2,a}$, which capture the impact of the policy on the probability of moving to a certain status for an employee belonging to age group a. We compute marginal effects to interpret results.

The constraint represented by the relatively low number of annual transitions by age group also prevents us from estimating a reliable version of model (2.4) which "freezes" employees' economic sector in 1998, neglecting employees entering the labor market after the policy change and further reducing the sample size.

Chapter 3

Trade, Migration and the Labor Market: Evidence from an Exchange Rate Shock

3.1 Introduction

Today's globalized world exhibits an increasing interdependence among economies, with trade and labor mobility representing two of the most prominent aspects of strengthening relationships. While close interconnections are undoubtedly among the key determinants of income growth and prosperity (Frankel and Romer, 2017), recent global crises have revealed their potential drawbacks due to higher levels of vulnerability to shocks. The intense economic and political debate fueled by growing integration has thus raised questions about the disruptive effects of these globalization shocks, especially on labor market outcomes.

A flourishing literature has devoted attention to the impact of trade shocks on workers' wages and employment, mostly focusing on the role of import competition (e.g., Autor et al., 2013, 2014). At the same time, several studies have analyzed the heterogeneous effects of variations in the inflow of immigrant workers, depending on their substitutability or complementarity with resident citizens (e.g., Borjas, 2003; Peri and Sparber, 2009; Ottaviano and Peri, 2012; Beerli et al., 2021). However, simultaneous changes in both the volumes of trade activities and the nationality composition of the workforce ask for a deeper analysis of the interactions between these shocks, especially concerning their joint impact on workers' outcomes.

This paper investigates how exposure to adverse trade shocks affects immigration flows and the substitutability between resident and incoming workers, in a context where moving costs that may hinder the relocation of foreign subjects are negligible. To examine how individual labor market outcomes respond to the interplay between changes in trade and immigration dynamics, I identify the groups of workers who bear most of the adjustment costs implied by the two shocks. Although the direct negative consequences of altered export competitiveness and import competition are experienced by manufacturing industries, this study further considers the effects that spill over into service sectors, where displaced workers may relocate to find a new employment (Dix-Carneiro and Kovak, 2019). This provides a more comprehensive view of the multiple underlying mechanisms shaping workers' outcomes.

To address these research questions, exchange rate movements represent an ideal case study, since they affect both the amount of traded goods and workers' migration decisions (Keita, 2016). This paper leverages as a natural experiment the sharp and persistent currency appreciation that followed the Swiss National Bank's decision to lift the minimum exchange rate of 1.20 Swiss Francs per Euro on January 15, 2015. This floor rate was introduced on September 6, 2011 to contrast the excessive appreciation of the Swiss Franc during the Euro crisis and triggered a period of stability in macroeconomic outcomes such as unemployment and GDP growth.

The repeal of this minimum exchange rate provides an extremely clean research setting due to the absence of anticipation effects, as documented by the flat profile of forward rates and option prices until the announcement of the policy change. This suggests that the Swiss National Bank was expected to continue enforcing the exchange rate floor, as officially declared at the end of 2014 (Jermann, 2017; Mirkov et al., 2019; Bonadio et al., 2020; Auer et al., 2021; Efing et al., 2023). Moreover, the subsequent Swiss Franc appreciation was perceived as permanent by economic agents, leading to persistent effects (Kaufmann and Renkin, 2017).

The Swiss labor market is a unique framework also because of the high share ($\approx$ 33%) of employed immigrants. In particular, regions close to the border exhibit a large fraction of workers who reside in neighboring countries and commute daily (or, more rarely, weekly) across the frontier. First, cross-border workers active in Switzerland take advantage of the sizeable wage differential with respect to their home countries and are extremely sensitive to exchange rate variations (Bello, 2020). For instance, currency appreciations imply an increase in the purchasing power of their earnings and, thus, a reduction in their reservation wages in Swiss Francs. Second, these workers' migration decisions are not constrained by large moving costs (Autor et al., 2013; Amior and Manning, 2018; Bartik and Rinz, 2018). Cross-border workers bear neither relocation costs – including non-pecuniary costs that arise when living farther from social networks and preferred local amenities – nor linguistic and skill barriers. Hence, the Swiss case study can be seen as a lab experiment that allows to estimate the size of relocation effects in the absence of the downward bias induced by prohibitive moving costs.

Combining rich information on trade flows with individual-level data from the Swiss Labor Force Survey and detailed statistics on cross-border workers' inflows in Switzerland, this paper presents two main sets of results, culminating in the analysis of the labor market effects induced by the interaction of shifts in both trade and immigration patterns.

First, I estimate the impact of changes in the volume of trade flows on workers' labor market outcomes in directly affected manufacturing sectors. After defining a measure of trade exposure that captures the vulnerability of each industry to import competition and losses of export competitiveness, I rely on a difference-in-differences approach that compares over time highly impacted sectors with their less exposed counterparts. Results show evidence of an increase in unemployment and a sizeable drop in earnings, conditional on the weekly number of hours worked. Both effects have a transitory nature and are mainly borne by individuals below age 30 and above age 50 employed in low-skilled occupations. Especially in the case of young subjects, job losses are mostly driven by non-registered unemployment, with displaced workers not eligible for unemployment benefits. By contrast, middle-aged workers exhibit a milder wage decrease and even a reduction in the probability of unemployment, likely as a result of their experience and firm-specific skills (Eichhorst et al., 2014). Using a difference-in-differences strategy at the labor market area level, I also report negative spillover effects on service sectors, especially for workers in low-skilled occupations and belonging to older age groups.

Second, this study documents that the Swiss Franc appreciation has led to an immediate and large rise in the share of immigrant cross-border workers in the labor force, especially in manufacturing industries. The magnitude and rapidity of this upward shift is indeed consistent with the absence of significant relocation costs for these cross-border workers when obtaining a job in Switzerland. Using a triple difference research design that further compares border and non-border labor market areas, I show that the increase in the share of cross-border workers is relatively larger in sectors characterized by a higher degree of trade exposure. This, in turn, leads to additional sizeable negative effects on residents' earnings and employment, especially for young individuals. Hence, the influx of cross-border workers, who are likely close substitutes for young residents, has implied an intensification of the impact of the trade shock. A steeper increase in the share of cross-border workers, with further negative effects on resident citizens' outcomes, is analogously observed in service sectors in border regions more exposed to the trade shock.

This paper relates to several strands of the literature, starting from the studies on the labor market impact of trade integration (e.g., Dauth et al., 2014). These works document the effects of import competition on employment, earnings, labor force participation, and population growth (Autor et al., 2013; Acemoglu et al., 2016; Greenland et al., 2019), with adverse consequences borne by employees with worse initial conditions and lower tenure (Autor et al., 2014). Focusing on exchange rate variations, it has been demonstrated that their impact on labor market outcomes is mediated by a variety of factors, including productivity, market power, technological development, openness to trade, and regulation (Campa and Goldberg, 2001; Klein et al., 2003; Berman et al., 2012; Alexandre et al., 2017).

The contribution of the present paper to this branch of works is twofold. First, I explore more closely the heterogeneity of the effects across generations, reporting that labor market outcomes not only deteriorate for young workers with lower tenure, but also for relatively older subjects, while middle-aged workers are shielded. Second, I show that exposure to immigration inflows is another crucial factor that determines the overall impact of a trade shock on workers' outcomes. While the existing evidence on immigrants' responsiveness to the impact of trade exposure is often biased by the presence of high moving costs that reduce immigrants' responsiveness (e.g., Autor et al., 2013), the peculiar Swiss setting exploited in this paper allows to estimate the actual effect that materializes in absence of relocation costs.

By estimating how effects spill over from manufacturing to service industries, I also add to the recently expanding evidence on the mechanisms of propagation of shocks across sectors, which so far have been mainly investigated in the field of automation (Acemoglu et al., 2020; Lerch, 2023).

Another growing line of research examines the relationship between labor demand and exchange rate fluctuations, showing that firms substitute labor with imported intermediate inputs when the latter become less expensive (Ekholm et al., 2012; Fauceglia et al., 2014). Kaiser and Siegenthaler (2016) document that the Swiss Franc appreciation during the Euro crisis led to a higher substitution of low-skilled workers with imported inputs in Switzerland, while high-skilled workers benefited from their complementarity with such inputs. Relatedly, Colella (2022) shows that the 2015 shock induced Swiss firms to rely on imported inputs to substitute workers performing offshorable routine tasks, expanding at the same time the demand for high-skilled workers.

I complement these findings by exploring a further channel, namely, the substitution between resident and immigrant workers.

Moreover, this paper extends the stream of literature on exchange rate variations as primary drivers of migration decisions (Keita, 2016), especially when workers have close ties with their home country. For instance, this applies to immigrants who are either sensitive to the purchasing power of remittances (Nekoei, 2013) or whose migration decisions are temporary (Dustmann and Görlach, 2016), as well as to cross-border workers (Bello, 2020; Albertini and Barisone, 2022). I contribute to this body of research by focusing on cross-border workers and examining whether exposure to negative trade shocks affects their employment, identifying the groups of resident citizens facing the effects of increased competition.

This paper speaks also to the studies on the impact of immigration on workers' labor market outcomes. Several scholars document that highly qualified immigrant workers foster productivity and wages due to their complementarity with physical capital (Lewis, 2011; Ottaviano et al., 2018), especially in the Swiss context (Beerli et al., 2021; Cristelli and Lissoni, 2020). However, resident workers may be harmed by a growing employment of immigrants who are close substitutes for them (Aepli and Kuhn, 2021; Gatti et al., 2022; Gentili and Mazzonna, 2023).

Finally, this paper enriches the wide literature on the price effects of the 2015 exchange rate shock in Switzerland. Existing works show that the sharp decline in the retail prices of goods imported from Euro countries has resulted in a larger share of expenditure allocated to buy them (Bonadio et al., 2020; Auer et al., 2021). At the same time, after the shock there is evidence of a decrease in Swiss firms' export growth (Auer et al., 2019) and of an improvement in the quality of exported goods (Freitag and Lein, 2023). This paper sheds light on a further mechanism, suggesting that firms located close to the border may have limited the losses of export competitiveness by reducing their production costs through the employment of cross-border workers willing to accept lower salaries.

From a policy perspective, this paper contributes to the ongoing debate on the heterogeneous labor market impact of trade and migration shocks, shedding light on the interaction of multiple mechanisms. This allows policymakers to design effective compensation measures to mitigate potential welfare losses and rising inequalities, targeting all workers who actually bear the consequences of shocks.

The remainder of this paper is organized as follows. Section 3.2 reports background information on the 2015 exchange rate shock and the role of cross-border workers in the

Swiss labor market. Section 3.3 describes the data and provides descriptive evidence on the evolution of both trade flows and the share of cross-border workers in the labor force. Section 3.4 outlines the empirical models. Section 3.5 discusses the results and the underlying mechanisms. Section 3.6 concludes.

3.2 Background

3.2.1 The 2015 exchange rate shock

This paper leverages as exogenous shock the sharp and persistent appreciation of the Swiss Franc against the Euro that followed the Swiss National Bank's unexpected decision to abandon the minimum exchange rate of 1.20 Swiss Francs per Euro on January 15, 2015.

This exchange rate floor was introduced after the outbreak of the Euro area sovereign debt crisis, on September 6^{th}, 2011, to limit the appreciation of the Swiss Franc generated by an increasing foreign demand of this currency as safe haven. Indeed, this measure aimed at preventing both a loss of export competitiveness and a rising level of import competition that could negatively affect production and employment. As a result, until the beginning of 2015 Switzerland was characterized by a period of substantial stability in terms of macroeconomic outcomes such as GDP growth, unemployment, interest and exchange rates.

Although the exchange rate floor was an exceptional and temporary measure to face a transitory period of uncertainty, the decision of the Swiss National Bank in January 2015 – partly driven by the forthcoming expansionary monetary policy of quantitative easing in the Euro area – was largely unanticipated by the forecasts of economic agents, who also perceived the subsequent currency appreciation as permanent (Kaufmann and Renkin, 2017).

Several studies document that the evolution of forward rates (i.e., interest rates for economic transactions taking place in the next future) and option prices (i.e., prices to acquire the right to buy or sell specific securities in the future) remained flat until the announcement of the monetary policy change on January 15, 2015 (Jermann, 2017; Mirkov et al., 2019; Bonadio et al., 2020; Auer et al., 2021). This suggests that economic agents' forecasts incorporated the declarations released in late 2014 by the Chairman of the Governing Board of the Swiss National Bank, who guaranteed the enforcement of the exchange rate floor (Jordan, 2014). Indeed, surveys conducted among economists by

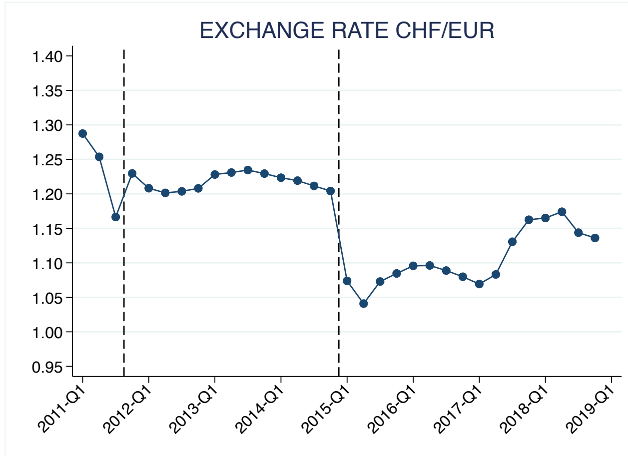


Figure 3.2.1: Evolution of the CHF/EUR exchange rate (2011–2019)

Notes: This figure shows the evolution over time (2011-2019) of the average exchange rate between the Swiss Franc and the Euro. The first vertical dashed line, before the last quarter of year 2011, identifies the beginning of the period characterized by the enforcement of the minimum exchange rate of 1.20 Swiss Francs per Euro introduced on September 6, 2011. The second vertical dashed line, before the first quarter of year 2015, identifies the beginning of the sharp appreciation of the Swiss Franc after the removal of the exchange rate floor on January 15, 2015.

Bloomberg immediately before the shock actually reveal that the event was unexpected (Bosley, 2015).

As reported in Figure 3.2.1, the immediate appreciation of the Swiss Franc by more than 20% was rather persistent over time. Until 2017, the value of the Swiss Franc against the Euro remained substantially higher with respect to the pre-shock period, on average by 16%. This implied a loss of competitiveness for Swiss exports, which became more expensive, and an increased import competition due to the availability of cheaper imported goods.

This exchange rate shock was extremely salient for the Swiss economy, since European countries are the main trade partners for Switzerland, accounting for approximately 70% of its imports and 50% of its exports (OECD, 2022). These figures acquire even more relevance considering that the overall value of Swiss trade flows exceeds 120% of the country's GDP, a share that doubles the OECD ($\approx$ 56%) and world ($\approx$ 58%) averages (World Bank, 2022). Such strong trade relationships are also the result of the high economic integration between Swiss border regions and their respective neighboring Euro countries, which is facilitated by the common linguistic background (Egger and Lassmann, 2015).

3.2.2 Cross-border workers in Switzerland

In the Swiss labor market, immigrant workers represent more than 30% of the labor force (Swiss Federal Statistical Office, 2022a). In border regions, a large fraction of these employees are cross-border workers, who continue to reside in their neighboring home countries, usually commuting on a daily basis. Cross-border workers account for almost 7% of the total workforce of the country, but in border regions their proportion is far more substantial, reaching 29% in the canton of Ticino and 24% in the canton of Geneva (Swiss Federal Statistical Office, 2021).

The labor supply of these workers has remarkably increased after the enactment of the *Agreement on the Free Movement of Persons* between Switzerland and the European Union in 2002, which granted them free access to the Swiss labor market, removing all the previously existing restrictions to labor mobility.

As they reside in neighboring Eurozone countries (roughly 55% of them live in France, 23% in Italy, 18% in Germany, and 3% in Austria), cross-border workers take advantage of the large wage differential between Switzerland and these states, where living costs are significantly lower. These workers are therefore highly sensitive to exchange rate variations that alter their purchasing power. The full responsiveness of their labor supply to exchange rate movements is facilitated by both the removal of all restrictions guaranteed by the *Agreement on the Free Movement of Persons* and the absence of relevant moving costs. Indeed, they need neither to relocate nor to face linguistic and skill barriers.

As for the economic sectors of employment, approximately two-thirds of cross-border workers are active in service sectors, while only one-third of them work in manufacturing industries, often in high-skilled occupations. However, the share of cross-border workers in the total workforce is larger in the secondary sector, due to the extremely high concentration of resident employees in service occupations (Swiss Federal Statistical Office, 2021).

3.3 Data

This section describes the different datasets combined for the empirical analysis, presenting also some descriptive evidence on the evolution over time of trade flows and immigrant cross-border workers' employment in Switzerland.

3.3.1 Data Sources

This paper leverages data on resident workers' labor market outcomes provided by the *Swiss Labor Force Survey* and information on the value of Swiss imports and exports released by the *Federal Office for Customs and Border Security* and the *Trade in Value Added Database* (OECD, 2022). Additional region- and sector-level data on employment and cross-border workers, plus further control variables, have been obtained from the *Swiss Federal Statistical Office*.

To ensure geographic representativeness, data are aggregated at the level of local labor market areas. These areas, called *spatial mobility regions*, are 106 subdivisions of the Swiss territory based on the concentration of economic activities and, in turn, commuting flows around a main location (Swiss Federal Statistical Office, 2005). The time horizon under analysis includes all years between 2011 and 2018. This time window allows to consider a period of economic stability before the 2015 exchange rate shock (see Section 3.2) and, at the same time, to focus on the subsequent years characterized by the persistent appreciation of the Swiss Franc.

Swiss Labor Force Survey

The main investigation of the labor market effects of the shock is based on the *Swiss Labor Force Survey* (SLFS), which covers a representative sample of the working age resident population (i.e., excluding cross-border workers) in Switzerland (Swiss Federal Statistical Office, 2022c) over the years 2011–2018, with each individual observed in two adjacent years.[1]

This dataset contains information on both sociodemographic characteristics (e.g., sex, age, education, nationality, marital status, number of children, residence) and employment status of the individual (e.g., employee, unemployed, retired).

The SLFS reports active individuals' occupation according to the *International Standard Classification of Occupations* (ISCO-08 code), the type of contract and the weekly number of hours worked. The data also include the 2-digit industry code (NOGA-08, based on the *Swiss General Classification of Economic Activities*) of the employing firm, as well as whether it is public or private.

[1]For the sake of clarity, note that since 2010 the survey is conducted quarterly, with different rotation groups. Individuals are interviewed twice per year in two subsequent years, with two different questionnaires every year (with either annual or quarterly variables). As the relevant variables are those included in the questionnaire with annual variables, the final dataset has an annual structure, with each individual included twice.

In case of unemployment, subjects who are registered in regional employment centres are distinguished from those who are not, therefore being not eligible for unemployment benefits. Additionally, the industry code of the last employing firm is provided.

The SLFS is further matched with SESAM (*Social Protection and Labor Market*) individual-level data, which report workers' gross and net annual nominal earnings (Swiss Federal Statistical Office, 2022b). These earnings are then expressed in real terms at 2014 prices, using the *Consumer Price Index* released by the *Swiss Federal Statistical Office*.

Appendix Table C.2.1 presents the summary statistics for the main variables of interest from the *Swiss Labor Force Survey*, differentiating the pre-shock period (2011–2014) from the after-shock period (2015–2018).

Import-Export Data

The evolution over time of Swiss imports and exports is investigated using detailed data provided by the *Federal Office for Customs and Border Security* (FOCBS). This dataset contains monthly information on quantities and monetary values (in Swiss Francs) of Swiss trade flows at postal-code level, by type of commodity (Harmonized System 6-digit classification) and by destination or origin country. I aggregate the data annually at the level of local labor market areas[2], focusing on transactions with non-zero quantities that are worth at least 1,000 Swiss Francs (Ariu, 2022).

Each HS 6-digit code is matched to both EUC (*End Use Categories*) and ISIC (*International Standard Industrial Classification*) codes (OECD, 2017). The EUC classification distinguishes between intermediate goods, final consumption goods, and capital goods. The ISIC 2-digit code identifies the sector that produces each commodity and fully corresponds to the Swiss General Classification of Economic Activities (NOGA, 2008 Nomenclature). It is worth underlining that these data cover only manufacturing sectors whose goods pass through customs offices.[3]

Appendix Table C.2.2 reports some descriptive statistics from the raw data on trade flows between Switzerland and Euro countries, showing the average annual monetary value (in millions of Swiss Francs, unadjusted for price and exchange rate changes) and the average annual number of traded commodities (according to the HS-6 digit

[2]Note that the information at postal code level may not be reliable in case of large depots located in small towns.

[3]Note that the primary sector (i.e., agriculture, forestry, fishing, mining, and quarrying) is excluded from the analysis.

classification). The table reports separate statistics for exports and imports, not only differentiating between intermediate, final, and capital goods, but also between the pre-shock (2011–2014) and the after-shock (2015–2018) period.

I exploit the *Input-Output Tables* (OECD, 2021) to collect information on the sector-specific level of *vertical specialization* in Switzerland, namely, on the share of the value of exported goods represented by imported inputs. This indicator measures the extent to which losses in export competitiveness after a currency appreciation can be counterbalanced by the availability of cheaper imported inputs. Further information on the sector-specific (2-digit industry code) value of Swiss imports and exports has been obtained from the *Trade in Value Added Database* (OECD, 2022).

Additional Data

The main datasets are complemented by additional municipal-level statistics released by the *Swiss Federal Statistical Office* on the total number of firms, employees, and cross-border workers by 2-digit NOGA-08 economic sector, as well as on the total resident population. Even in this case, data are aggregated at the level of local labor market areas, which are also differentiated depending on their distance from the nearest border-crossing office (see Appendix Figure C.1.1).[4]

Appendix Table C.2.3 reports the average number of cross-border workers and the corresponding share in the total workforce in the pre-shock (2012–2014) and after-shock period (2015–2018), focusing also on the border region using various thresholds for the maximum distance from the frontier (i.e., 10, 20, and 30 km).

Additional canton-level data on the number of residence permits (B, C, L) and working permits for cross-border workers (G) have been obtained from the *Swiss State Secretariat for Migration*. Furthermore, when analyzing the values of Swiss imports and exports, sector-specific (2-digit industry code) price deflators will be used to isolate changes in traded quantities from changes in prices (Swiss Federal Statistical Office, 2020). Specifically, the *import price index* (IPI) accounts for price changes of both imported products that reach consumers and imported intermediate inputs used by firms in the production process. The *producer price index* (PPI), instead, measures price changes of goods produced in Switzerland and sold in the country or abroad. Price deflators are rescaled choosing 2014 as base year.

[4] I use geodata released by the *Swiss Federal Office of Topography* to compute the Euclidean distance between the centroid of each labor market area and the closest border-crossing office, focusing only on offices open all year round.

Further data from the *Swiss Federal Statistical Office* include statistics on gross production, value added, and total wage bill for each industry.

3.3.2 The evolution over time of Swiss trade flows

Figure 3.3.1 illustrates the dynamics over time of the volume of trade flows between Switzerland and Euro countries. It plots the time coefficients from a regression model for the logarithm of the annual monetary value of goods produced in a given manufacturing sector and exported or imported by each Swiss labor market area.

To isolate the effect of quantity changes from price fluctuations, the monetary values of export and import flows are adjusted using, respectively, the *producer price index* and the *import price index* as price deflators.[5] In addition to indicator variables for each year between 2012 and 2018, excluding 2014 as reference year, the model includes sector and region fixed effects.

The estimates displayed in Figure 3.3.1 show a large (5 percentage points) immediate reduction in exports (blue squares) after the Swiss Franc appreciation. At the same time, the amount of imported final consumption goods (red triangles) and capital goods (orange circles) increases sharply (up to, respectively, 9 and 8 percentage points in 2017). Although to a lesser extent, there is also a relevant rise (reaching 4 percentage points in 2016) in the quantity of imported intermediate inputs (green diamonds).

Appendix Figure C.1.2 suggests that these effects are actually driven by changes in the quantities of previously traded goods, as the average number of different commodities (at HS-6 digit code level) does not change after the shock.[6]

Appendix Figure C.1.3 documents the limited impact of the shock on trade flows with non-Euro partners, presenting a stable pattern for exports and an already growing pre-trend for imports, likely driven by the enactment of the free trade agreement between Switzerland and China in 2013.

Finally, Appendix Figure C.1.4 explores potential differences between border and non-border regions. While the increase in imports is largely comparable, the drop in exports is reabsorbed earlier in border areas, where a slight rebound effect seems also to materialize since 2017.

[5]Note that the actual increase in imported quantities from Euro trade partners after 2015 might be even larger, as the *import price index* reflects also countries with currencies whose exchange rates with the Swiss Franc were relatively less affected by the shock.

[6]There is also no effect in terms of potential substitutions across years (i.e., commodities that are not traded any more and replaced by other commodities with a different HS-6 code).

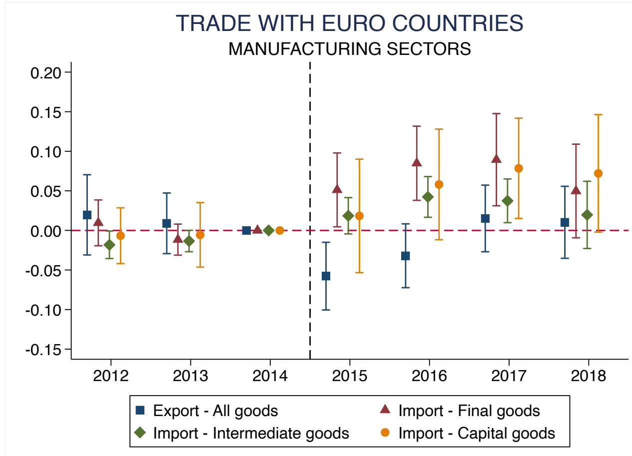


Figure 3.3.1: Swiss trade flows with Euro countries (2012–2018)

Notes: This figure plots the time coefficients for each year between 2012 and 2018 from a regression model for the logarithm of the annual monetary value of goods produced in a given manufacturing sector and exported or imported by each Swiss labor market area, with confidence intervals at the 5% significance level. Monetary values are deflated using the *producer price index* and *import price index* in case of exports and imports, respectively. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. The model is estimated separately for exports (blue squares), imported final consumption goods (red triangles), imported intermediate inputs (green diamonds), and imported capital goods (orange circles). All specifications include sector and region fixed effects. Robust standard errors are clustered at the sector level and estimates are weighted for the region-level population size. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

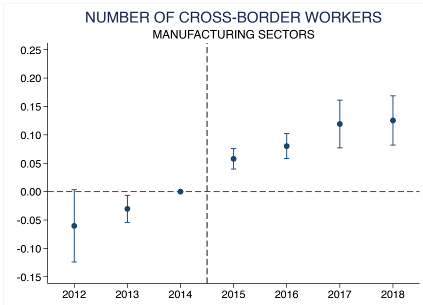
3.3.3 Cross-border workers in Switzerland

Evaluating the effect of a currency appreciation on the employment of immigrant cross-border workers in the labor market is an empirical issue, since the overall impact depends on the interplay of two opposite mechanisms.

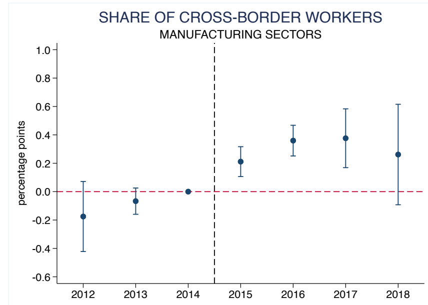
On the one hand, the decrease in exports and the growing import competition lead to shrinking production and, in turn, reduced labor demand. On the other hand, firms may have an incentive to rely more on cross-border workers, whose reservation wages in Swiss Francs become lower as a result of the 2015 shock.

Figure 3.3.2 shows the time coefficients from a regression model for the annual (log) number and share of cross-border workers in each sector and region. As in the case of trade flows, the model includes an indicator variable for every year between 2012 and 2018 (excluding 2014 as reference year), plus sector and region fixed effects.

Focusing on manufacturing sectors directly affected by the changes in trade flows described in Section 3.3.2, Figure 3.3.2 documents the continuously rising number of active cross-border workers, with a growth pattern which tends to become even steeper



(a)



(b)

Figure 3.3.2: (Log) number and share of cross-border workers in Switzerland - Manufacturing Sectors (2012–2018)

Notes: This figure plots the time coefficients for each year between 2012 and 2018 from a regression model for the logarithm of the number (panel a) and the share (panel b) of cross-border workers in a given manufacturing sector and Swiss labor market area, with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. The specification includes sector and region fixed effects. Robust standard errors are clustered at sector level and estimates are weighted for the within-region employment size of each sector. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

after 2015 (panel a). As a result, there is evidence of a sizeable increase in the share of cross-border workers in the total workforce after the exchange rate shock, especially between 2015 and 2017 (panel b).

Thus, despite the overall economic contraction due to the reduced volume of exports and the strengthened import competition, the employment opportunities for cross-border workers in manufacturing sectors have continued to expand. Whether this effect is driven by the substitution of more expensive resident workers in sectors more exposed to the adverse trade shock will be the research question addressed in the next empirical investigation.

Appendix Figure C.1.5 further shows that a steadily increasing number and share of cross-border workers in the labor market can be observed when service sectors are also included in the analysis.[7]

3.4 Empirical Strategy

This section outlines the empirical strategy adopted to investigate the impact of changes in the volume of trade flows on workers' labor market outcomes and the further effects

[7]On the contrary, Appendix Figure C.1.6 shows a decrease in the number of residence permits for foreign citizens after 2015 (see Albertini and Barisone, 2022).

driven by the increased influx of cross-border workers. First, I describe the difference-in-differences models used to estimate the effects of trade exposure in manufacturing industries and their spillovers in service sectors. Second, I present the triple difference model that also compares border and non-border regions to assess whether trade exposure affects the employment of cross-border workers, estimating the additional effects on residents' outcomes.

In what follows, I illustrate the index that measures the degree of trade exposure of each manufacturing sector. This index is based on differences in the volume of import and export flows exhibited by each sector before the occurrence of the exchange rate shock and is computed according to the following expression:

$$\tau_s = \frac{e_{s,2012-14} \cdot (1 - n_s) + i_{s,2012-14}}{v_{s,2012-14}}$$

In this index, $e_{s,2012-14}$ is the average value of exports of sector s towards Euro countries over the period 2012–2014, n_s is the sector-specific share of exports value represented by imported intermediate inputs (OECD, 2021), $i_{s,2012-14}$ is the average value of imports of final goods produced by sector s in Euro countries in years 2012–2014, and $v_{s,2012-14}$ is the average total value of gross production of sector s in Switzerland over the same time window. The index is normalized between 0 and 1.

The rationale behind τ_s is as follows. First, an industry is more vulnerable if in the pre-shock period it was highly dependent on foreign demand, therefore exporting a large share of its produced goods. This exposure is mitigated by the inclusion of imported intermediate inputs in exports, as a currency appreciation implies a reduction in their price. Second, the vulnerability to the shock increases if sector s was already facing intense import competition for its produced goods prior to the shock. In this case, it is relatively easier to further expand the imports of final goods exploiting already existing contracts.

According to this index, more exposed sectors include those involved in the production of textiles, vehicles, machinery and electrical equipment, plastic and metal products, and chemicals (Appendix Table C.2.4, Index 1). As a robustness check (Section 3.5.4), different versions of τ_s have been considered. In all cases, either the index is unchanged or the relative exposure of the different sectors remains unaffected, as all indices are extremely correlated (Appendix Table C.2.5).

3.4.1 Estimating direct and spillover effects of trade exposure

To evaluate the impact of the shock on labor market outcomes in directly affected manufacturing sectors, I estimate the following multiperiod diff-in-diff model:

$$y_{is\ell t} = \beta_0 + \sum_{k=2011}^{2018} \beta_k \, \tau_s \cdot \mathbb{1}[t = k] + \psi^T X_{it} + \lambda_s + \chi_\ell + \mu_t + \epsilon_{is\ell t} \tag{3.1}$$

where $y_{is\ell t}$ is the logarithm of the net annual earnings at 2014 prices or the unemployment status of individual i in manufacturing sector s, region ℓ, and year t.

Each individual is exposed to the shock depending on the economic sector of the employing firm (or, in case of unemployment, of the last employing firm). Such exposure is measured by index τ_s, rescaled by its 10-90 percentile range to ease the interpretation of coefficients. This continuous treatment variable is interacted with an indicator variable $\mathbb{1}[t = k]$ for each year t. The omitted reference year is 2014, the year before the shock. Hence, the coefficients β_ks (k = 2011, ..., 2013, 2015, ..., 2018) measure the dynamic impact of the shock on resident workers' outcomes.

The model includes sector (λ_s) and labor market area (χ_ℓ) fixed effects that account for time-invariant differences across sectors and regions, respectively. Year fixed effects (μ_t) capture aggregate fluctuations over time. The vector of controls X_{it} includes sex, marital status, number of children, a quadratic polynomial for age, a dummy variable for tertiary education, a dummy variable for Swiss nationality, and – only when earnings are the outcome – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. The error term $\epsilon_{is\ell t}$ captures unobservable time-varying shocks. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights.

To estimate the spillover effects in service sectors, the identification strategy then shifts to the labor market area level. This analysis investigates whether regions with a higher concentration of exposed manufacturing industries also experience a deterioration of labor market outcomes in service sectors, as a result of both an economic contraction and a stronger competition with displaced workers previously employed in manufacturing firms. The exposure measure for each labor market area, denoted as ϕ_ℓ, is computed as a region-level weighted average of the sector-level index τ_s (see Appendix Figure C.1.7). Weights $\omega_{s\ell}$ reflect the shares of total manufacturing employment absorbed by each manufacturing industry in every region:

$$\phi_\ell = \sum_s \omega_{s\ell} \cdot \tau_s$$

After rescaling the index ϕ_ℓ by its 10-90 percentile range, I use it as treatment variable in the following multiperiod diff-in-diff model for individual labor market outcomes in service sectors:

$$y_{is\ell t} = \gamma_0 + \sum_{k=2011}^{2018} \gamma_k \, \phi_\ell \cdot \mathbb{1}[t = k] + \psi^T X_{it} + \lambda_s + \chi_\ell + \mu_t + \epsilon_{is\ell t} \tag{3.2}$$

The structure of this model is analogous to that of model (3.1), with the time coefficients γ_ks now capturing the local spillover effects of trade exposure on earnings and unemployment probability in service sectors.

Finally, I estimate a static specification of models (3.1) and (3.2), in which the treatment variable τ_s or ϕ_ℓ is interacted with two time dummy variables, the first one for the two years immediately after the shock (i.e., 2015 and 2016) and the second one for the following two years (i.e., 2017 and 2018).

3.4.2 Estimating the effect of exposure to trade and migration

As anticipated in Section 3.3.3, the exchange rate shock impacts also the share of cross-border workers employed in Swiss regions close to the frontier. To analyze how these changes in immigrant workers' labor supply interact with exposure to variations in the pattern of import and export flows, I rely on a triple difference estimator (Olden and Møen, 2022). Specifically, I estimate an alternative static version of models (3.1) and (3.2) that further compares border and non-border labor market areas. This research design allows for an assessment of the additional impact on resident workers' labor market outcomes potentially driven by the substitutability with immigrant cross-border workers.

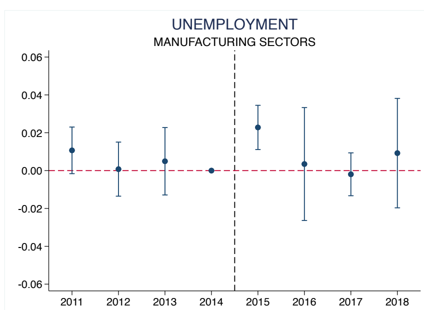
To investigate more deeply the mechanism underlying these effects, I evaluate whether the increase in the share of employed cross-border workers is larger in sectors and regions with higher trade exposure by estimating the triple difference models (excluding individual-level covariates) for the proportion of cross-border workers in the total workforce of region ℓ, sector s, and year t.

3.5 Results

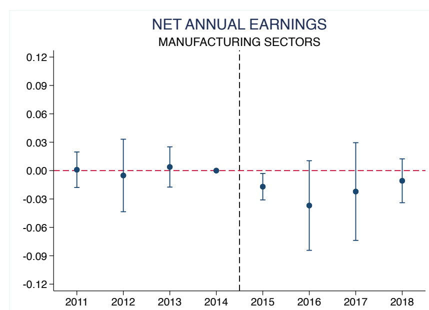
Section 3.5.1 analyzes the impact of exposure to reduced export competitiveness and increased import competition on resident workers' unemployment and real earnings in manufacturing industries. Section 3.5.2 examines the spillover effects on labor market outcomes in service sectors. Section 3.5.3 investigates whether higher levels of trade exposure lead to larger increases in the employment of cross-border workers, estimating the further impact on residents' outcomes.

3.5.1 The impact of trade exposure on manufacturing sectors

Figure 3.5.1 shows the estimates from the dynamic difference-in-differences model (3.1) for resident workers' probability of unemployment and net annual earnings at 2014 prices, with 95% confidence intervals.



(a)



(b)

Figure 3.5.1: Resident Workers' Labor Market Outcomes - Manufacturing Sectors – Dynamic DiD model (2011–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors. Panel (a) shows the effect of the shock on resident employees' probability of unemployment and panel (b) shows the effect on the logarithm of resident employees' real net annual earnings at 2014 prices. Each graph shows the estimates of the coefficients β_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

Resident workers in manufacturing industries with higher exposure to the trade shock experience an immediate increase in unemployment probability (panel a) and a decline in earnings (panel b) relative to their counterparts in less affected sectors. The magnitude of these effects is sizeable. Rescaling τ_s by its 10-90 percentile range, the coefficients displayed in Figure 3.5.1 document that an increase in the exposure index from 8% to 38% is associated to a 2.3 percentage point increase in unemployment in 2015 and a 4 percentage point earnings drop in 2016.

Figure 3.5.1 clearly depicts the temporary nature of these effects, which materialize in 2015 and gradually fade by the end of 2017, mirroring the dynamics of the Swiss Franc appreciation against the Euro reported in Figure 3.2.1.

Consistently with the previous literature, Appendix Table C.2.6 shows that the negative wage effect is driven by workers in low-skilled occupations. Moreover, Appendix Figure C.1.8 suggests that rising unemployment is mainly explained by non-registered unemployment, with part-time workers more exposed to the risk of job loss.

Table 3.5.1 investigates the heterogeneity of these effects in manufacturing sectors across age groups. Column (1) displays the coefficients from the static specification of model (3.1) for the full sample of workers, while Columns (2)–(4) report separate estimates by age group (18–30; 31–49; 50–64).[8]

Although coefficients are not statistically significant, results suggest an increase in unemployment probability for workers below age 30 and above age 50 (Panel A, Columns 2 and 4). By contrast, the likelihood of unemployment becomes lower for middle-aged individuals (Panel A, Column 3). As reported in Appendix Table C.2.7, these two opposite effects can be mostly attributed to rising non-registered and decreasing registered unemployment, respectively.

At the same time, younger and older workers exhibit a drop in earnings of up to 5 and 4.3 percentage points (Panel B, Columns 2 and 4), whereas the negative effect for middle-aged subjects is smaller and less persistent (Panel B, Column 3).

Appendix Table C.2.8 indicates that the deterioration of labor market outcomes described so far is almost entirely due to stronger import competition rather than to reduced export competitiveness. This finding is explained by the structure of Swiss exports, which are mainly technologically advanced goods characterized by low price elasticities (Thorbecke and Kato, 2018) and continuous upgrades in their quality, also driven by the 2015 shock itself (Freitag and Lein, 2023).

[8] Note that the dynamic model (3.1) cannot be estimated separately by age group due to the relatively low number of observations (i.e., 16%) in manufacturing sectors in the SLFS.

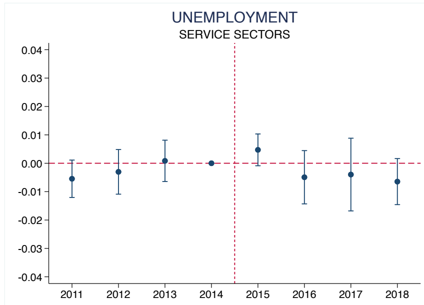
Table 3.5.1: Resident Workers' Labor Market Outcomes - Manufacturing Sectors (2011-2018)

	(1) All	(2) Age 18-30	(3) Age 31-49	(4) Age 50-64
Panel A: Unemployment				
$\tau_s \times \mathbb{I}[2015, 2016]$	0.009	0.030	-0.017*	0.024
	(0.009)	(0.026)	(0.009)	(0.017)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.000	-0.004	0.006	-0.014
	(0.005)	(0.010)	(0.016)	(0.009)
N	42212	5880	21651	14681
Panel B: Earnings				
$\tau_s \times \mathbb{I}[2015, 2016]$	-0.027**	-0.050*	-0.028**	-0.028*
	(0.008)	(0.024)	(0.009)	(0.014)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.016	-0.032*	0.012	-0.043***
	(0.010)	(0.016)	(0.017)	(0.011)
N	34536	5041	18201	11293

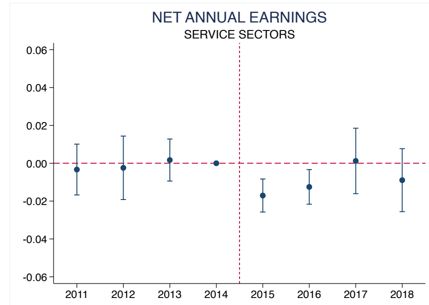
Notes: This table shows the estimates of a *static* version of model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Panel A refers to the impact of the shock on the probability of unemployment, while panel B refers to the logarithm of real net annual earnings at 2014 prices. Column (1) does not distinguish between age groups, while Columns (2)-(4) focus on different age groups (18–30; 31–49; 50–64). All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

3.5.2 Spillover effects in service sectors

The next results focus on service sectors, documenting the spillover effects of trade exposure stemming from manufacturing industries. Figure 3.5.2 shows the dynamic impact of the shock on resident workers' probability of unemployment and real net annual earnings, reporting the coefficients estimated from model (3.2) with the corresponding 95% confidence intervals.



(a)



(b)

Figure 3.5.2: Resident Workers' Labor Market Outcomes - Non-Manufacturing Service Sectors – Dynamic DiD model (2011–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.2) for the labor market outcomes of resident subjects in Switzerland who are active in private non-manufacturing sectors. Panel (a) shows the effect of the shock on resident employees' probability of unemployment and panel (b) shows the effect on the logarithm of resident employees' real net annual earnings at 2014 prices. Each graph shows the estimates of the coefficients γ_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, a dummy variable for part-time work, and a dummy variable for high-skilled occupations. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

Workers in service sectors in exposed regions experience a transitory increase in unemployment probability (panel a)[9] and a reduction in earnings relative to their counterparts in less impacted areas (panel b). While these effects are smaller than those observed in manufacturing sectors, their magnitude is still considerable. Rescaling ϕ_ℓ by its 10-90 percentile range, coefficients indicate that a 25 percentage point increase in exposure leads to an immediate rise in unemployment of roughly 0.5 percentage points and to a decrease in earnings that reaches 2 percentage points.

Appendix Table C.2.9 shows that the adverse impact on earnings is driven by low-skilled occupations, which are indeed more exposed to higher competition with displaced workers from manufacturing industries (Dix-Carneiro and Kovak, 2019).

Moreover, Appendix Table C.2.10 suggests that the negative spillover effects in service sectors are mostly borne by workers above age 50, while young workers seem

[9] Appendix Figure C.1.9 also distinguishes between registered and non-registered unemployment, suggesting that in service sectors the shock mostly affected the former.

relatively shielded. Actually, Appendix Table C.2.11 reveals a sizeable drop in earnings for low-educated young workers in low-skilled occupations, which is masked in the overall sample by the wage gains obtained by individuals with tertiary education employed in high-skilled occupations.[10]

3.5.3 Trade exposure and immigration inflows

Building on the evidence reported in the previous sections, the following analysis investigates the relationship between trade exposure and changes in the employment of cross-border workers, estimating the additional effects on residents' outcomes.

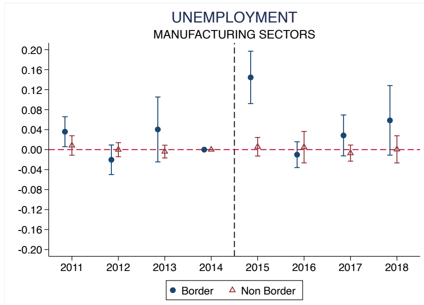
Following the literature (Bello, 2020; Beerli et al., 2021), Swiss border regions exposed to the inflow of cross-border workers are here defined as those whose centroid has a maximum distance of 10 kilometers from the closest border crossing office.

Figure 3.5.3 presents separate estimates from model (3.1) for border and non-border regions to analyze the differences between them in the effects of trade exposure on resident workers' outcomes in manufacturing sectors. According to these coefficients, the immediate rise in the unemployment probability is almost entirely explained by the large increase in border regions (panel a). Results suggest that unemployment grows in border regions also after 2017, likely as a result of the substitutability between residents and incoming cross-border workers. At the same time, the drop in earnings in highly exposed manufacturing sectors is remarkably more pronounced in border regions (panel b). As it will be discussed more in detail below, these effects are mostly driven by young resident workers.

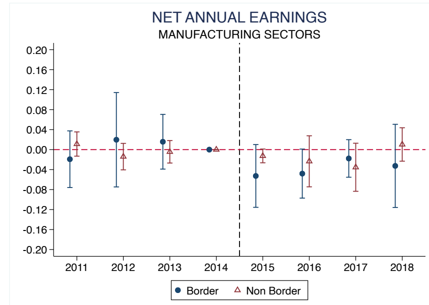
To shed light on the mechanism underlying these effects, Figure 3.5.4 also displays separate estimates from model (3.1) for border and non-border regions when the share of cross-border workers in the labor force in a given sector and area is used as dependent variable (and individual-level covariates are thereby excluded). These coefficients show that border regions exhibit a far larger increase in the share of cross-border workers in manufacturing sectors more affected by import competition and losses of export competitiveness.

Focusing on labor market areas close to the frontier over the whole time window 2015-2018, these estimates document that an increase in the index of trade exposure from 8% to 38% is associated with a sizeable 6.2 percentage point increase in the share

[10] This can be explained by the increasing supply of tertiary education motivated by the rising labor demand for highly qualified workers, especially in R&D occupations (Schultheiss et al., 2023).



(a)



(b)

Figure 3.5.3: Resident Workers' Labor Market Outcomes - Manufacturing Sectors – Dynamic DiD model - Border vs. Non-Border (2011–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors, separately for border and non-border regions. Panel (a) shows the effect of the shock on the probability of unemployment and panel (b) shows the effect on the logarithm of real net annual earnings at 2014 prices. Each graph shows the estimates of the coefficients β_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, a dummy variable for part-time work, and a dummy variable for high-skilled occupations. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

of cross-border workers in the labor force. At the country level, an analogous rise in the exposure measure would still lead to a statistically significant increase of 1.6 percentage points.

It is worth mentioning here that this empirical analysis does not distinguish between the roles played by labor demand and supply in driving such changes in the workforce composition. The observed effect is likely the result of the interplay of both the rising labor supply of cross-border workers willing to take advantage of larger real wage differentials and the growing demand of less costly employees that may allow firms to limit competitiveness losses.

Table 3.5.2 reports the estimates from a triple difference specification of the static version of model (3.1), also by age group. For the sake of clarity, it only displays the interactions between τ_s and the time dummy variables, plus the further interactions with the dummy for border regions. All the coefficients on other interaction terms are neither statistically significant nor economically relevant. These estimates document

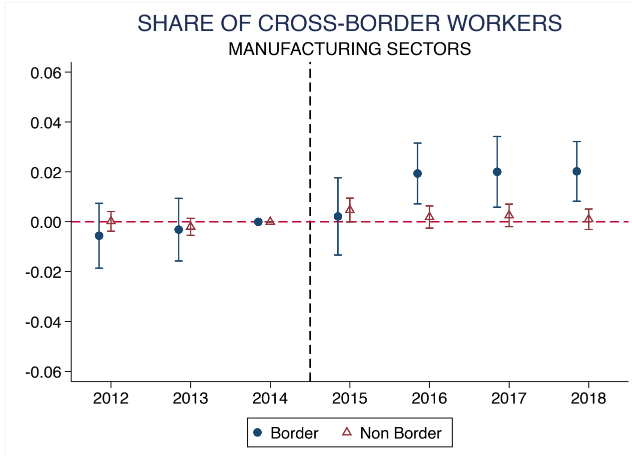


Figure 3.5.4: Share of Cross-Border Workers - Manufacturing Sectors – Dynamic DiD model - Border vs. Non-Border (2012–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.1) for the share of cross-border workers in the labor force in private manufacturing sectors in Switzerland, distinguishing between border and non-border regions. The graph shows the estimates of the coefficients β_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

that the overall negative impact of the trade shock on resident workers' outcomes in manufacturing sectors is more pronounced in border regions (Column 1). In particular, young individuals in border areas experience both a higher increase in the probability of unemployment (Panel A, Column 2) and a larger drop in earnings (Panel B, Column 2) relative to their counterparts in non-border areas.

Table 3.5.3 then presents the estimates obtained when the outcome variable of the triple difference model is the share of cross-border workers in the total employment. These coefficients corroborate the evidence presented in Figure 3.5.4, documenting a statistically significant increase in the share of cross-border workers employed in manufacturing sectors with higher trade exposure in the whole country, an effect that acquires a far larger magnitude in border areas.

Focusing on service sectors, Appendix Table C.2.12 shows evidence of a massive drop in earnings for young workers in border regions after 2015. This effect is partially mitigated in areas with higher trade exposure, where young individuals face an increased likelihood of unemployment. The opposite is true for middle-aged workers,

Table 3.5.2: Resident Workers' Outcomes - Manufacturing Sectors
Triple Difference Estimator (2011-2018)

	(1) All	(2) Age 18-30	(3) Age 31-49	(4) Age 50-64
Panel A: Unemployment				
$\tau_s \times \mathbb{I}[2015, 2016]$	0.005	-0.003	-0.015	0.031
	(0.007)	(0.028)	(0.008)	(0.019)
$\tau_s \times \mathbb{I}[2015, 2016] \times$ border	0.036	0.155*	-0.011	-0.058
	(0.048)	(0.069)	(0.034)	(0.041)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.002	-0.010	0.011	-0.017
	(0.005)	(0.019)	(0.018)	(0.012)
$\tau_s \times \mathbb{I}[2017, 2018] \times$ border	0.014	0.022	-0.024	0.061
	(0.011)	(0.023)	(0.019)	(0.074)
N	42212	5880	21651	14681
Panel B: Earnings				
$\tau_s \times \mathbb{I}[2015, 2016]$	-0.021**	-0.034	-0.027**	-0.023
	(0.009)	(0.029)	(0.009)	(0.016)
$\tau_s \times \mathbb{I}[2015, 2016] \times$ border	-0.045**	-0.116**	0.007	-0.048
	(0.018)	(0.040)	(0.046)	(0.055)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.017	-0.026	0.006	-0.040**
	(0.011)	(0.019)	(0.017)	(0.016)
$\tau_s \times \mathbb{I}[2017, 2018] \times$ border	0.012	-0.058	0.042	-0.060
	(0.032)	(0.048)	(0.027)	(0.051)
N	34536	5041	18201	11293

Notes: This table shows the estimates of a *static* version of model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors, accounting also for the role of distance from the border using a triple difference estimator. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Border labor market areas are those whose centroid has a distance from the nearest border crossing office of at most 10 kilometers. Panel A refers to the impact of the shock on the probability of unemployment, while panel B refers to its impact on the logarithm of real net annual earnings at 2014 prices. Column (1) does not distinguish between age groups, while Columns (2)-(4) focus on different age groups (18–30; 31–49; 50–64). All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table 3.5.3: Share of Cross-Border Workers - Manufacturing Sectors
Triple Difference Estimator (2012-2018)

	(1)
$\tau_s \times \mathbb{I}[2015, 2016]$	0.006***
	(0.002)
$\tau_s \times \mathbb{I}[2015, 2016] \times$ border	0.012*
	(0.006)
$\tau_s \times \mathbb{I}[2017, 2018]$	0.005**
	(0.002)
$\tau_s \times \mathbb{I}[2017, 2018] \times$ border	0.021***
	(0.005)
N	8861

Notes: This table shows the estimates of a *static* version of model (3.1) for the share of cross-border workers in the total employment of private manufacturing sectors, accounting also for the role of distance from the border using a triple difference estimator. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Border labor market areas are those whose centroid has a distance from the nearest border crossing office of at most 10 kilometers. The model includes sector, labor market area, and year fixed effects, as well as a region-specific linear time trend. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

as the growing unemployment probability in border areas is attenuated in regions more affected by the trade shock, where a decline in earnings is observed. An analogous effect emerges for older workers after 2017.

3.5.4 Robustness Checks

As anticipated in Section 3.4, as a first robustness check I compute alternative versions of τ_s using the average values of exports, imports, and production over the years 2013–2014 rather than 2012–2014 (Index 2 in Appendix Table C.2.4), or using directly the values of years 2012 (Index 3 in Appendix Table C.2.4) and 2014 (Index 4 in Appendix Table C.2.4). In all cases, the index remains substantially unchanged. Other versions of τ_s have been obtained using as denominator the average value added (Index 5 in Appendix Table C.2.4) or the average total wage bill (Index 6 in Appendix Table C.2.4) of each sector rather than its gross production, but also including all trade flows rather than only those with Euro countries (Index 7 in Appendix Table C.2.4). In all these cases, the relative degree of exposure of the different manufacturing sectors is unaffected.

As also reported in Appendix Table C.2.5, all these versions of the index exhibit an extremely high degree of correlation.

For instance, Figure C.1.10 reports the estimated coefficients for equation (3.1) when the treatment variable is the index constructed using as denominator the average value added instead of gross production (i.e., Index 5 in Appendix Table C.2.4). Both for unemployment and net real annual earnings, the coefficients are consistent with those reported in Figure 3.5.1, although sometimes less precisely estimated.

As a further robustness check, I replicate the analysis using an index of trade exposure computed over a time window that is excluded when investigating labor market outcomes. I estimate model (3.1) over the years 2013–2018 using as treatment variable the index based on the values of exports, imports, and production in 2012 (Index 3 in Appendix Table C.2.4). Even in this case, the coefficients displayed in Appendix Figure C.1.11 are not different from those presented in Figure 3.5.1.

Furthermore, when examining how the effect of the trade shock in manufacturing industries spills over to service sectors, I estimate model (3.2) including all workers from both groups of sectors. The coefficients displayed in Appendix Figure C.1.12 mirror the dynamics reported in Figures 3.5.1 and 3.5.2, suggesting that the effects observed in manufacturing and service sectors tend to be aligned. However, it is worth noting that the obtained estimates are extremely close to those for service sectors, which indeed absorb the vast majority of the workforce in Switzerland.

Panels (a) and (b) of Appendix Figure C.1.13 document that the negative spillover effects shown in Figure 3.5.2 for employees in service sectors are not substantially altered when an alternative region-level exposure index ϕ_ℓ is constructed. In the main specification (3.2), this index was computed as a weighted average of sector-level exposure measures (τ_s) weighted for the shares of total manufacturing employment absorbed in every region by each manufacturing industry. Now, instead, weights are represented by the shares of total employment absorbed by those manufacturing sectors, thus taking into account the relevance of the secondary sector in the local economy. Panels (c) and (d) of Appendix Figure C.1.13 also show the coefficients obtained when both manufacturing and service sectors are included in the analysis, confirming the estimates displayed in Appendix Figure C.1.12.

As for the relationship between trade exposure and changes in the employment of cross-border workers in manufacturing sectors, I then restrict the attention to border labor market areas and estimate model (3.1) for both the share and number of cross-border workers, excluding individual-level covariates. Appendix Figure C.1.14 confirms a steeper increase in the share of cross-border workers in industries with higher degrees of trade exposure (panel a). Such effect is explained by the rising number of incoming cross-border workers combined with the growing unemployment among resident workers. Actually, the growth rate of the number of cross-border workers does not substantially vary across sectors with different levels of trade exposure (panel b). Hence, there is no statistically significant drop in the hiring rate of cross-border workers in sectors facing an economic contraction, which even exhibit a higher initial number of employed cross-border workers before the shock.

Focusing on service sectors, Appendix Figure C.1.15 also documents that border regions with a higher degree of exposure to the trade shock have experienced a larger increase in the share of cross-border workers in the labor force since 2015 (panel a). The effect is particularly sizeable in 2015, the year characterized by a relevant increase in unemployment for resident workers (Figure 3.5.2, panel a). However, as expected, the rise in the number of cross-border workers is lower in regions more affected by the economic contraction with respect to the other border areas (panel b).

Appendix Figure C.1.16 further shows that, although coefficients become smaller, these dynamics for the shares of cross-border workers in manufacturing and service sectors are confirmed when border regions are defined using a threshold distance of 20 kilometers between their centroid and the nearest border crossing office.

3.6 Conclusions

This paper investigates how exposure to adverse trade shocks is associated with changes in the intensity of immigration inflows, studying how workers' labor market outcomes are in turn affected. To address this research question, I leverage the sharp and persistent Swiss Franc appreciation that followed the Swiss National Bank's unexpected decision to lift the exchange rate floor with the Euro on January 15, 2015. This exchange rate shock implies large exogenous variation in both the volume of trade flows and the labor supply of immigrant cross-border workers in Switzerland. In particular, these workers are fully responsive to exchange rate variations, as they can benefit from relevant wage gains without facing any substantial relocation costs. Hence, the Swiss setting provides a sort of ideal lab experiment to evaluate the impact of a trade shock on workers' flows.

Combining trade data with information from the Swiss Labor Force Survey, I show evidence of a temporary decline in earnings and rise in (non-registered) unemployment in manufacturing industries characterized by high exposure to losses of export competitiveness and intensified import competition. This effect, which also spills over to service sectors, is mainly borne by young and relatively old subjects. I then document a far larger increase in the share of cross-border workers in sectors and areas more exposed to the trade shock. This implies further detrimental effects on residents' outcomes, especially among young workers. The inflow of cross-border workers, coupled with the rising risk of unemployment faced by residents, suggests that firms close to the frontier have tended to limit the competitiveness losses due to the shock by substituting the local workforce with foreign employees willing to accept lower nominal wages.

These findings contribute to the wide economic literature and the extensive policy debate on the impact of potential shocks in today's globalized world. By exploring the role of negative trade shocks as drivers of changes in the degree of substitutability between resident and incoming immigrant workers, this paper sheds light on an additional mechanism that has been neglected so far. Moreover, it identifies groups of workers who are either harmed or shielded from these shocks.

This study has two main implications. First, especially in presence of high rates of labor mobility, estimating the overall impact of a trade shock on workers' outcomes requires considering the effects due to simultaneous changes in immigration patterns. Second, effective labor market policies designed to mitigate the consequences of trade shocks should target the most exposed groups of workers and consider the multiple underlying mechanisms through which they may be affected. This opens the path to future research that focuses on developing the most appropriate policy instruments to limit the vulnerability of workers' labor market outcomes to globalization shocks.

Appendix C

C.1 Additional Figures

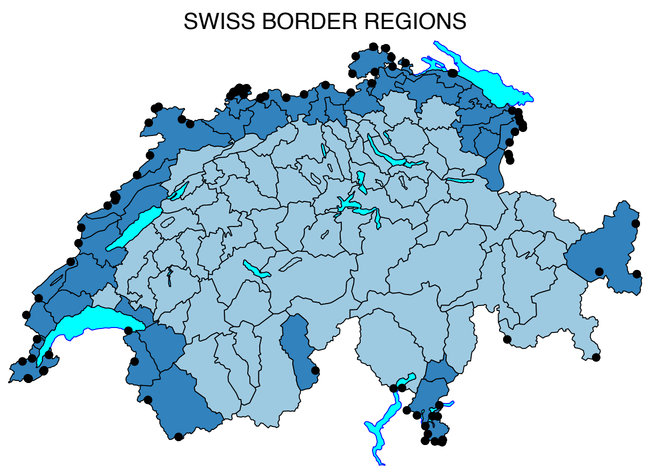
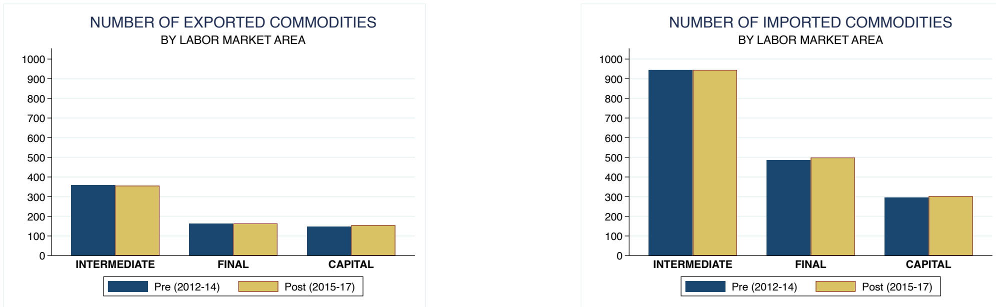


Figure C.1.1: Swiss Border Regions

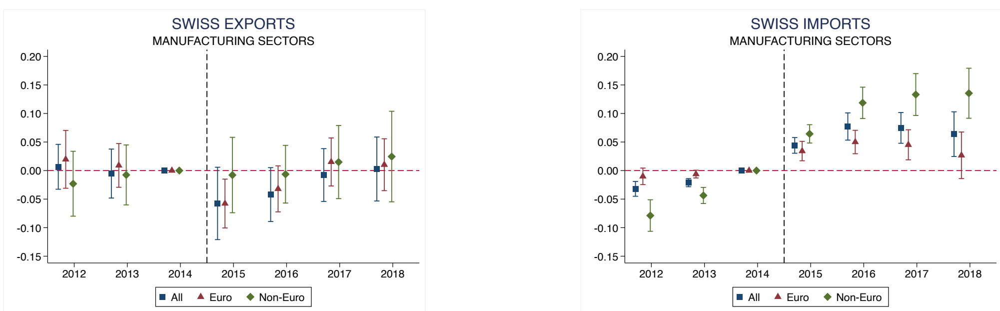
Notes: This map shows border and non-border Swiss labor market areas, using a threshold of 20 kilometers for the maximum distance between the centroid of each region and the nearest border-crossing office. Border-crossing offices (open all year, 24 hours per day) are represented by black dots on the border.



(a) (b)

Figure C.1.2: Average number of different traded commodities (2012–2017)

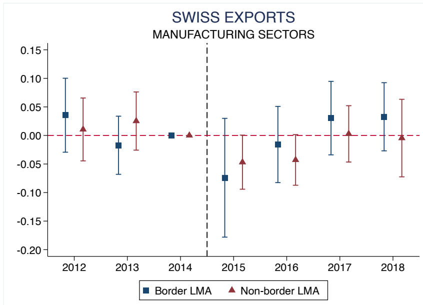
Notes: This figure compares the average annual number of commodities (at HS6-digit code) that each Swiss labor market area exported to (panel a) or imported from (panel b) Euro countries before (2012–14) and after (2015–18) the shock, distinguishing between intermediate inputs, final consumption goods, and capital goods.



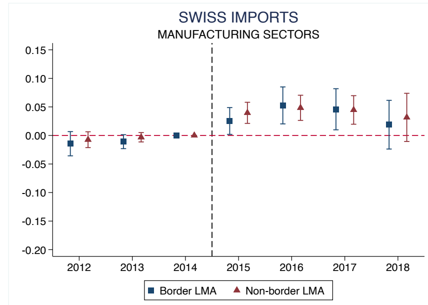
(a) (b)

Figure C.1.3: Swiss trade flows with Euro *vs.* non-Euro partners (2012–2018)

Notes: This figure plots the time coefficients for each year between 2012 and 2018 from a regression model for the logarithm of the annual monetary value of goods produced in a given manufacturing sector and exported or imported by each Swiss labor market area, with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. The model is estimated separately for exports (panel a) and imports (panel b). In each panel, coefficients are reported both when the model is estimated considering all trade flows (blue squares) and when the analysis is restricted separately to trade flows with Euro (red triangles) and non-Euro (green diamonds) countries. All specifications include sector and region fixed effects. Robust standard errors are clustered at the sector level and estimates are weighted for the region-level population size. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



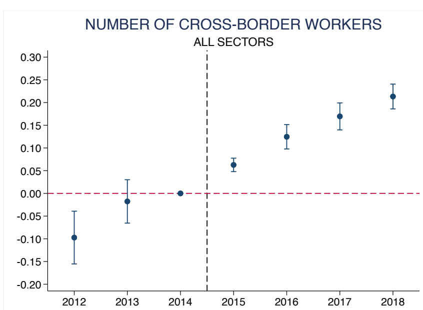
(a)



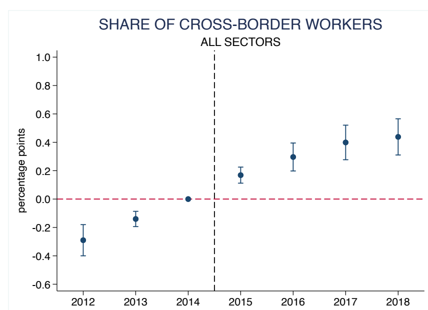
(b)

Figure C.1.4: Swiss trade flows with Euro countries - Border vs. non-border labor market areas (2012–2018)

Notes: This figure plots the time coefficients for each year between 2012 and 2018 from a regression model for the logarithm of the annual monetary value of goods produced in a given manufacturing sector and exported or imported by each Swiss labor market area, with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. The model is estimated separately for exports (panel a) and imports (panel b). In each panel, coefficients are reported separately for border (blue squares) and non-border (red triangles) labor market areas. Border labor market areas are defined as those whose centroid has a maximum distance of 20 kilometers from the closest border-crossing office. All specifications include sector and region fixed effects. Robust standard errors are clustered at the sector level and estimates are weighted for the region-level population size. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the exchange rate shock.



(a)



(b)

Figure C.1.5: (Log) number and share of cross-border workers in Switzerland - Manufacturing and Service Sectors (2012–2018)

Notes: This figure plots the time coefficients for each year between 2012 and 2018 from a regression model for the logarithm of the number (panel a) and the share (panel b) of cross-border workers in a given manufacturing sector and Swiss labor market area, with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. The specification includes sector and region fixed effects. Robust standard errors are clustered at sector level and estimates are weighted for the within-region employment size of each sector. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

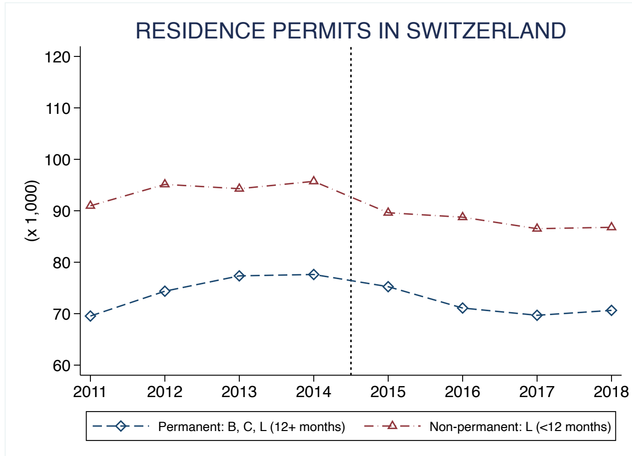


Figure C.1.6: Number of residence permits in Switzerland (2011–2018)

Notes: This figure shows the evolution over time of the number of new residence permits for foreign citizens released in Switzerland between 2011 and 2018, based on the information provided by the *Swiss State Secretariat for Migration*. Permanent permits (i.e., B, C, and L) are valid for more than one year, while non-permanent permits (i.e., L) have a maximum duration of 12 months. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

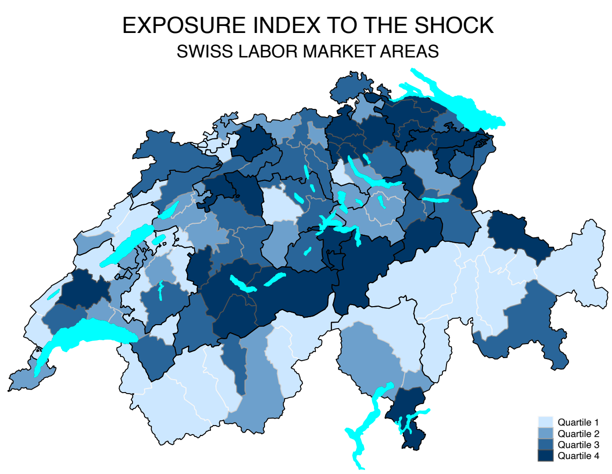
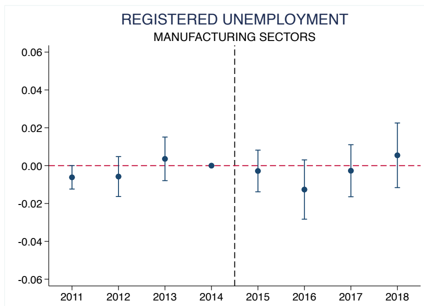
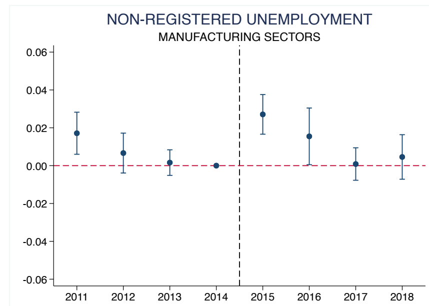


Figure C.1.7: Index of exposure to the shock at the level of labor market areas

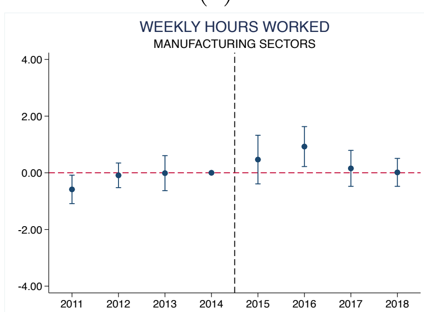
Notes: This figure shows the variation in the intensity of exposure to the shock of Swiss labor market areas, based on the index ϕ_ℓ presented in Section 3.4. This index is a weighted average of the sector-level exposure index τ_s, using as weights the share of employees absorbed by each sector in a given labor market area. The values taken by the index, ranging between 0.16 and 0.37, have been subdivided in four quartiles.



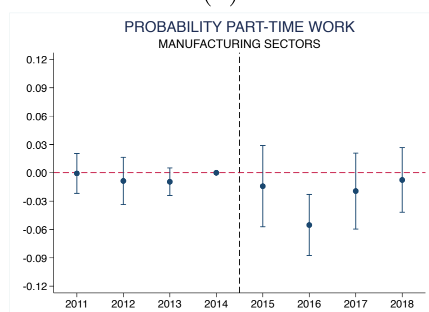
(a)



(b)



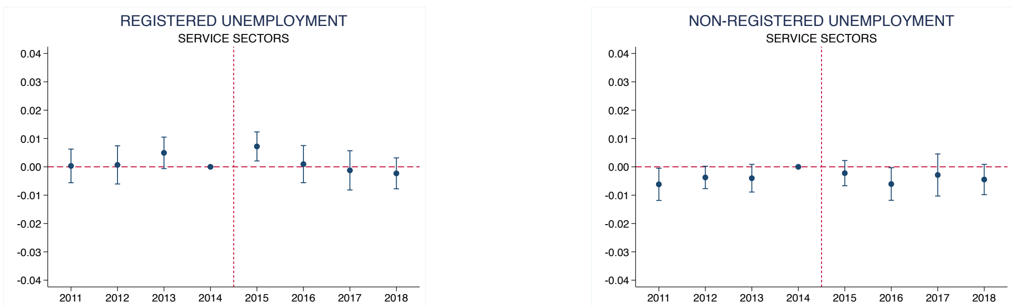
(c)



(d)

Figure C.1.8: Resident Workers' Labor Market Outcomes - Manufacturing Sectors – Dynamic DiD model (2011–2018)

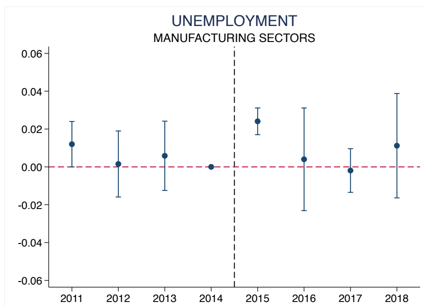
Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors. Panels (a) and (b) show the effect of the shock on resident employees' probability of registered and non-registered unemployment, respectively. Panel (c) and (d) focus on the number of weekly hours worked and the probability to work part-time, respectively. Each graph shows the estimates of the coefficients β_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for education, a dummy variable for Swiss nationality, and a quadratic polynomial for age. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



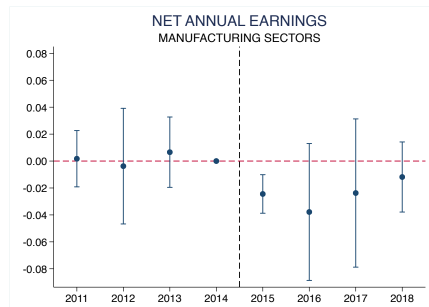
(a) (b)

Figure C.1.9: Resident Workers' Unemployment - Non-Manufacturing Service Sectors – Dynamic DiD model (2011–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.2) for the probability of unemployment of resident subjects in Switzerland who are active in private service sectors. Panel (a) shows the effect of the shock on resident employees' probability of registered unemployment, while panel (b) shows the effect of the shock on resident employees' probability of non-registered unemployment. Each graph shows the estimates of the coefficients γ_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, and a dummy variable for Swiss nationality. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



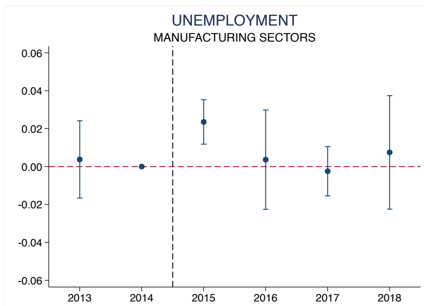
(a)



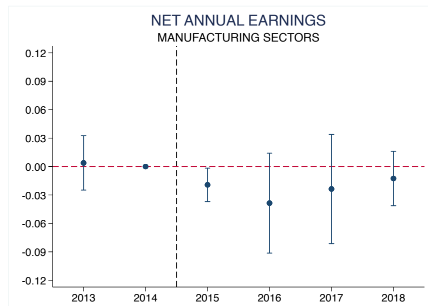
(b)

Figure C.1.10: Resident Workers' Labor Market Outcomes - Manufacturing Sectors – Dynamic DiD model - Alternative Sector-level Exposure Index (2011–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors. As a robustness check, in this case the exposure index τ_s is constructed using as denominator the value added rather than the total value of production (Index 4 in Appendix Table C.2.4). Panel (a) shows the effect of the shock on resident employees' probability of unemployment and panel (b) shows the effect on the logarithm of resident employees' real net annual earnings at 2014 prices. Each graph shows the estimates of the coefficients β_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



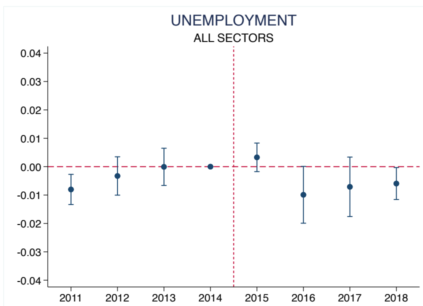
(a)



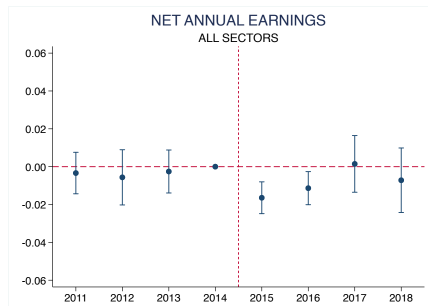
(b)

Figure C.1.11: Resident Workers' Labor Market Outcomes - Manufacturing Sectors – Dynamic DiD model - Out-of-sample Index (2013–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors. As a robustness check, the exposure index τ_s is constructed using the values of exports, imports, and production for year 2012 (Index 3 in Appendix Table C.2.4), while the estimates are derived for the subsequent years 2013–2018. Panel (a) shows the effect of the shock on resident employees' probability of unemployment and panel (b) shows the effect on the logarithm of resident employees' real net annual earnings at 2014 prices. Each graph shows the estimates of the coefficients β_k (k = 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



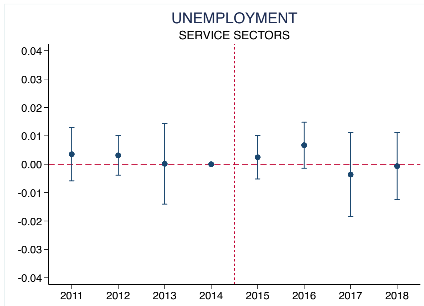
(a)



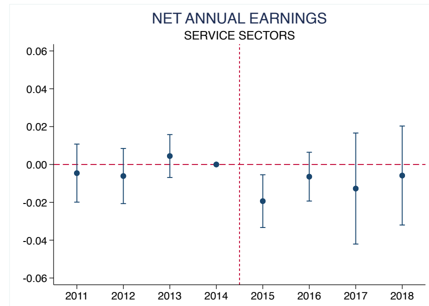
(b)

Figure C.1.12: Resident Workers' Labor Market Outcomes - Manufacturing and Service Sectors – Dynamic DiD model (2011–2018)

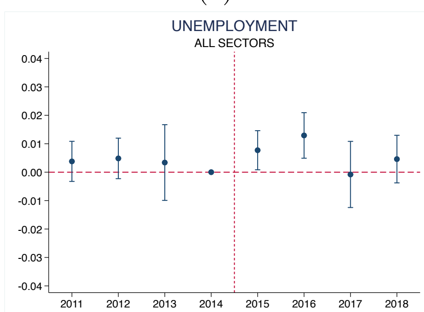
Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.2) for the labor market outcomes of resident subjects in Switzerland who are active in all private sectors. Panel (a) shows the effect of the shock on resident employees' probability of unemployment and panel (b) shows the effect on the logarithm of resident employees' real net annual earnings at 2014 prices. Each graph shows the estimates of the coefficients γ_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



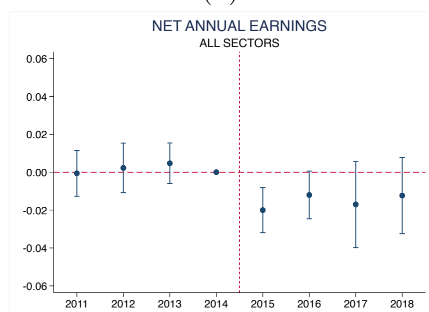
(a)



(b)



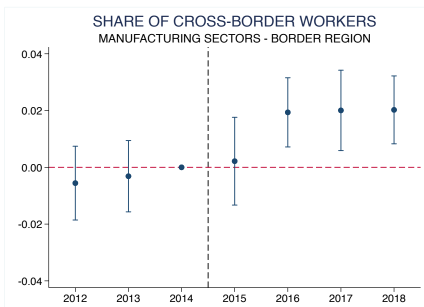
(c)



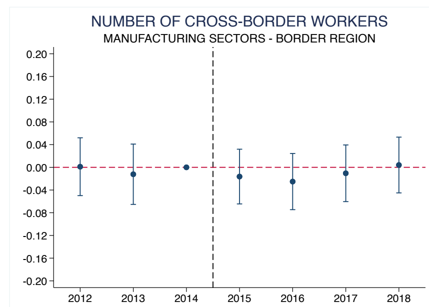
(d)

Figure C.1.13: Resident Workers' Labor Market Outcomes – Dynamic DiD model - Alternative Region-level Exposure Index (2011–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.2) for the labor market outcomes of resident subjects in Switzerland who are active in private sectors. Focusing on service sectors, panel (a) shows the effect of the shock on resident employees' probability of unemployment and panel (b) shows the effect on the logarithm of resident employees' real net annual earnings at 2014 prices. Focusing on both manufacturing and service sectors, panel (c) shows the effect of the shock on resident employees' probability of unemployment and panel (d) shows the effect on the logarithm of resident employees' real net annual earnings at 2014 prices. Each graph shows the estimates of the coefficients γ_k (k = 2011,..., 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



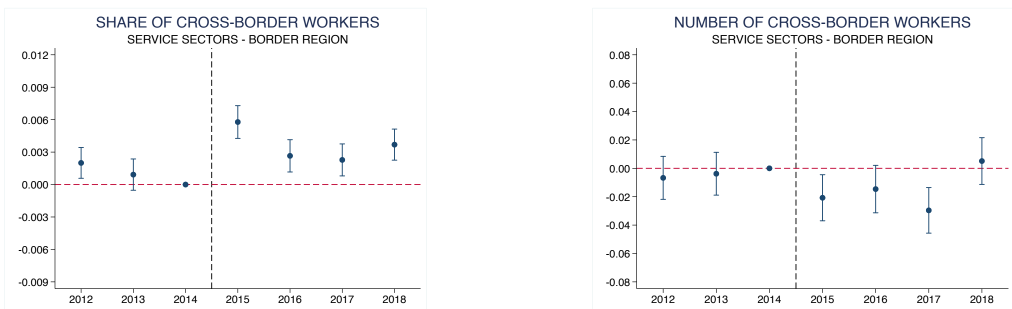
(a)



(b)

Figure C.1.14: Share and Number of Cross-Border Workers - Manufacturing Sectors - Dynamic DiD model (2012–2018)

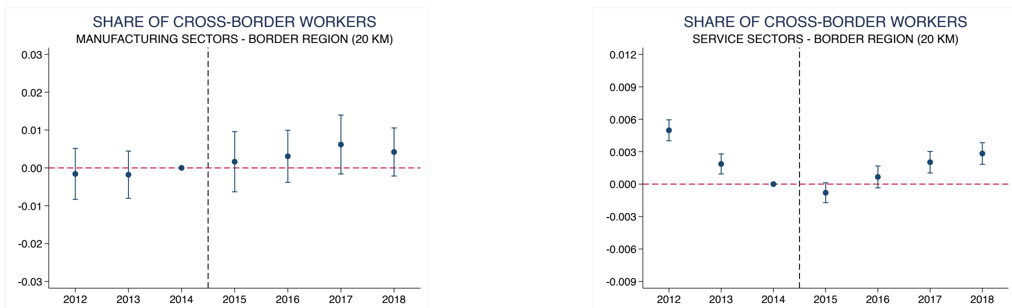
Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.1) – excluding individual-level covariates – for the share and number of cross-border workers in manufacturing sector s, labor market area ℓ, and year t. Panel (a) shows the differential effect of the trade shock across sectors on the share of cross-border workers in the labor force, while panel (b) shows the effect on the logarithm of their absolute number. The model is estimated for border labor market areas, namely, those whose centroid has a distance from the nearest border crossing office of at most 10 kilometers. Each graph shows the estimates of the coefficients β_k (k = 2012, 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects. Robust standard errors are two-way clustered at sector *times* region and year level. Estimates are weighted for the share of employment absorbed by sector s in each area ℓ. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



(a) (b)

Figure C.1.15: Share and Number of Cross-Border Workers - Service Sectors - Dynamic DiD model (2012–2018)

Notes: This figure shows the estimates from the dynamic difference-in-differences model (3.2) – excluding individual-level covariates – for the share and number of cross-border workers in service sector s, labor market area ℓ, and year t. Panel (a) shows the differential effect of the trade shock across sectors on the share of cross-border workers in the labor force, while panel (b) shows the effect on the logarithm of their absolute number. The model is estimated for border labor market areas, namely, those whose centroid has a distance from the nearest border crossing office of at most 10 kilometers. Each graph shows the estimates of the coefficients γ_k (k = 2012, 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects. Robust standard errors are two-way clustered at sector *times* region and year level. Estimates are weighted for the share of employment absorbed by sector s in each area ℓ. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.



(a) (b)

Figure C.1.16: Share of Cross-Border Workers - Manufacturing and Service Sectors - Threshold: 20 Km - Dynamic DiD model (2012–2018)

Notes: The two panels of this figure show, respectively, the estimates from the dynamic difference-in-differences models (3.1) and (3.2) – excluding individual-level covariates – for the share of cross-border workers in sector s, labor market area ℓ, and year t. Panel (a) shows the differential effect of the trade shock across sectors on the share of cross-border workers in the labor force in manufacturing sectors, while panel (b) refers to service sectors. The model is estimated for border labor market areas, namely, those whose centroid has a distance from the nearest border crossing office of at most 20 kilometers. Each graph shows the estimates of the coefficients β_k or γ_k (k = 2012, 2013, 2015, ..., 2018), with confidence intervals at the 5% significance level. The last year before the occurrence of the exchange rate shock (i.e., 2014) is the omitted year. All models include sector, labor market area, and year fixed effects. Robust standard errors are two-way clustered at sector *times* region and year level. Estimates are weighted for the share of employment absorbed by sector s in each area ℓ. The vertical dashed line (between 2014 and 2015) indicates the beginning of the period following the shock.

C.2 Additional Tables

Table C.2.1: Summary Statistics - Swiss Labor Force Survey (2011-2018)

	(1) Overall	(2) 2011–2014	(3) 2015–2018
Share of Females	49.86%	49.92%	49.80%
	(0.5000)	(0.5000)	(0.5000)
Average Age	41.22	41.10	41.34
	(13.00)	(12.99)	(13.00)
Share Non-Swiss	40.39%	38.43%	42.28%
	(0.4907)	(0.4864)	(0.4940)
Share Married	50.88%	51.50%	50.28%
	(0.4999)	(0.4998)	(0.5000)
Share Tertiary Education	32.45%	29.76%	35.04%
	(0.4682)	(0.4572)	(0.4771)
Share Manufacturing Sector	10.83%	11.06%	10.62%
	(0.3109)	(0.3137)	(0.3081)
Share of Unemployed	7.24%	7.08%	7.40%
	(0.2591)	(0.2564)	(0.2617)
Share of Non-Registered Unemployed	2.05%	1.99%	2.11%
	(0.1418)	(0.1397)	(0.1437)
Average Weekly Hours Worked	35.30	35.38	35.22
	(12.15)	(12.29)	(12.03)
Share Part-Time Workers	37.44%	36.57%	38.26%
	(0.4840)	(0.4816)	(0.4860)
Share High-Skilled Occupations	51.31%	49.53%	53.01%
	(0.4998)	(0.5000)	(0.4991)
Average Net Annual Earnings	61'935.57	60'906.95	62'891.36
	(36'668.92)	(36'648.76)	(36'661.91)
N	382'379	196'826	185'553

Notes: This table shows descriptive statistics for the variables of interest included in the *Swiss Labor Force Survey*, showing average values over the full time window 2011–2018 (Column 1), over the pre-shock period 2011–2014 (Column 2) and over the after-shock period 2015–2018 (Column 3). Standard deviations in parentheses. All statistics are computed using sample weights provided by the *Swiss Labor Force Survey*.

Table C.2.2: Swiss Trade Flows with Euro Countries (2011-2018)

	(1) Overall	(2) 2011–2014	(3) 2015–2018
Panel A: Exports			
Intermediate Goods			
Average Total Value (mln. CHF)	50’058.34	50’224.52	49’892.17
Average Number of Commodities (HS-6 digit)	2’705	2’732	2’677
Final Goods			
Average Total Value (mln. CHF)	19’464.85	18’950.06	19’979.64
Average Number of Commodities (HS-6 digit)	1’026	1’029	1’022
Capital Goods			
Average Total Value (mln. CHF)	11’911.94	11’792.18	12’031.69
Average Number of Commodities (HS-6 digit)	628	630	626
Panel B: Imports			
Intermediate Goods			
Average Total Value (mln. CHF)	52’169.03	54’143.97	50’194.1
Average Number of Commodities (HS-6 digit)	2’928	2’946	2’911
Final Goods			
Average Total Value (mln. CHF)	24’097.48	24’021.81	24’173.16
Average Number of Commodities (HS-6 digit)	1’164	1’165	1’162
Capital Goods			
Average Total Value (mln. CHF)	14’050.41	14’356.18	13’744.64
Average Number of Commodities (HS-6 digit)	638	637	638

Notes: This table shows the descriptive statistics for trade flows between Switzerland and Euro countries, separating exports (Panel A) and imports (Panel B), but also distinguishing between intermediate, final, and capital goods. The table reports the average annual monetary value (in millions of Swiss Francs) and the average annual number of traded commodities (according to the HS-6 digit classification), based on the data released by the *Federal Office for Customs and Border Security*. Average annual values are computed over the full time window 2011–2018 (Column 1), over the pre-shock period 2011–2014 (Column 2), and over the after-shock period 2015–2018 (Column 3).

Table C.2.3: Cross-Border Workers in Switzerland (2012-2018)

	(1) Overall	(2) 2012–2014	(3) 2015–2018
All Switzerland	6.14%	5.91%	6.37%
	(289’490)	(273’506)	(305’474)
Border Region - 10 km	20.61%	19.98%	21.23%
	(215’000)	(204’896)	(225’104)
Border Region - 20 km	14.31%	13.85%	14.78%
	(254’114)	(241’501)	(266’726)
Border Region - 30 km	8.82%	8.52%	9.12%
	(280’368)	(265’527)	(295’208)

Notes: This table reports the average annual share of cross-border workers in the total workforce (and the average annual absolute number of cross-border workers) in Switzerland over the full time window 2012–2018 (Column 1), over the pre-shock period 2012–2014 (Column 2) and over the after-shock period 2015–2018 (Column 3), using the data released by the *Swiss Federal Statistical Office*. The table reports statistics for the whole country and for the border region. As for the border region, results are reported considering three different thresholds, namely, including labor market areas whose centroid has a maximum distance from the nearest border-crossing office of at most 10, 20, and 30 kilometers.

Table C.2.4: Sector-Level Exposure Index (τ_s) - Manufacturing Sectors

NOGA-08 Code	Sector	Index 1	Index 2	Index 3	Index 4	Index 5	Index 6	Index 7
10-12	Food products, beverages and tobacco	0.1539	0.1583	0.1449	0.1458	0.4570	0.9628	0.2895
13-15	Textiles, textile products, leather and footwear	0.6776	0.6629	0.7074	0.6280	1.7479	2.9320	1.6280
16	Wood and products of wood and cork	0.0753	0.0750	0.0760	0.0679	0.1943	0.2737	0.1159
17-18	Paper products and printing	0.1605	0.1624	0.1568	0.1456	0.3683	0.5645	0.2720
19	Coke and refined petroleum products	0.1787	0.1715	0.1931	0.1541	0.6805	2.1150	0.2299
20-21	Chemicals and pharmaceutical products	0.1830	0.1827	0.1836	0.1777	0.5251	2.2900	0.5299
22	Rubber and plastics products	0.3251	0.3282	0.3187	0.3103	0.8363	1.1905	0.5567
23	Other non-metallic mineral products	0.0915	0.0930	0.0882	0.0862	0.2147	0.4086	0.1992
24	Basic metals	0.1733	0.1749	0.1700	0.1671	0.5147	0.9272	0.4334
25	Fabricated metal products	0.1438	0.1473	0.1367	0.1308	0.2953	0.4561	0.2884
26	Computer, electronic and optical equipment	0.1807	0.1794	0.1837	0.1540	0.4627	1.2029	0.5825
27	Electrical equipment	0.2730	0.2714	0.2760	0.2460	1.0033	1.9076	0.5549
28	Machinery and equipment	0.3830	0.3757	0.3983	0.3708	0.9701	1.6783	0.8025
29	Motor vehicles, trailers and semi-trailers	1.7832	1.7345	1.8777	1.7551	4.3707	10.6261	2.6251
30	Other transport equipment	0.4861	0.4925	0.4732	0.4519	1.2551	2.4825	1.0718
31-33	Repair and installation of machinery and equipment	0.1713	0.1698	0.1746	0.1643	0.4113	0.7068	0.4247

Notes: This table presents the value of the index τ_s for each manufacturing sector. Index 1 corresponds to the baseline definition (Section 3.4): $\tau_s = \frac{e_{s,2012-14} \cdot (1-n_s) + i_{s,2012-14}}{p_{s,2012-14}}$, where $e_{s,2012-14}$ is the average value of exports of sector s towards Euro countries over the period 2012–2014, n_s is the sector-specific share of exports value represented by imported intermediate inputs, $i_{s,2012-14}$ is the average value of imports of final goods produced by sector s in Euro countries over the period 2012–2014, and $v_{s,2012-14}$ is the average total value of gross production of sector s over years 2012–2014. Index 2 is based on the average values of exports, imports, and production over years 2013–2014 rather than 2012–2014. Index 3 is based on the values of exports, imports, and production of year 2012. Index 4 is based on the values of exports, imports, and production of year 2014. Index 5 and index 6 are alternative versions of index 1 that use as denominator, respectively, the average value added and the average wage bill of the sector instead of its average gross value of production. Finally, index 7 considers all exports and imports of Switzerland, not only trade flows with Euro countries.

Table C.2.5: Correlation across different sector-level exposure indices

Exposure Index	Index 1	Index 2	Index 3	Index 4	Index 5	Index 6	Index 7
Index 1	1.00						
Index 2	1.00	1.00					
Index 3	1.00	1.00	1.00				
Index 4	1.00	1.00	1.00	1.00			
Index 5	1.00	0.99	1.00	0.99	1.00		
Index 6	0.97	0.97	0.97	0.97	0.98	1.00	
Index 7	0.96	0.97	0.96	0.96	0.96	0.92	1.00

Notes: This table reports the degree of correlation across the alternative versions of the exposure index τ_s for each manufacturing sector. Index 1 corresponds to the baseline definition (Section 3.4): $\tau_s = \frac{e_{s,2012-14} \cdot (1-n_s) + i_{s,2012-14}}{p_{s,2012-14}}$, where $e_{s,2012-14}$ is the average value of exports of sector s towards Euro countries over the period 2012–2014, n_s is the sector-specific share of exports value represented by imported intermediate inputs, $i_{s,2012-14}$ is the average value of imports of final goods produced by sector s in Euro countries over the period 2012–2014, and $v_{s,2012-14}$ is the average total value of gross production of sector s over years 2012–2014. Index 2 is based on the average values of exports, imports, and production over years 2013–2014 rather than 2012–2014. Index 3 is based on the values of exports, imports, and production of year 2012. Index 4 is based on the values of exports, imports, and production of year 2014. Index 5 and index 6 are alternative versions of index 1 that use as denominator, respectively, the average value added and the average wage bill of the sector instead of its average gross value of production. Finally, index 7 considers all exports and imports of Switzerland, not only trade flows with Euro countries.

Table C.2.6: Resident Workers' Earnings by Skill Level of Occupation - Manufacturing Sectors (2011-2018)

	(1) All	(2) Low-Skilled	(3) High-Skilled
$\tau_s \times \mathbb{I}[2015, 2016]$	-0.027**	-0.037**	-0.004
	(0.008)	(0.014)	(0.017)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.016	-0.014	0.002
	(0.010)	(0.017)	(0.016)
N	34536	18772	15695

Notes: This table shows the estimates of a *static* version of model (3.1) for the logarithm of net real annual earnings (at 2014 prices) of resident subjects in Switzerland who are active in private manufacturing sectors. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the occurrence of the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Column (1) reports the estimates for all workers, while Columns (2) and (3) focus on, respectively, low-skilled and high-skilled occupations (*International Standard Classification of Occupations*). All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. Significance levels: *** p $<$ 0.01; ** 0.01 $\leq$ p $<$ 0.05; * 0.05 $\leq$ p $<$ 0.10.

Table C.2.7: Resident Workers' Unemployment - Manufacturing Sectors (2011-2018)

	(1) All	(2) Age 18-30	(3) Age 31-49	(4) Age 50-64
Panel A: Registered Unemployment				
$\tau_s \times \mathbb{I}[2015, 2016]$	-0.006	-0.011	-0.019**	0.015
	(0.007)	(0.011)	(0.007)	(0.008)
$\tau_s \times \mathbb{I}[2017, 2018]$	0.004	0.018*	-0.005	-0.002
	(0.003)	(0.008)	(0.010)	(0.002)
N	41683	5684	21445	14554
Panel B: Non-Registered Unemployment				
$\tau_s \times \mathbb{I}[2015, 2016]$	0.015**	0.039	0.002	0.012
	(0.006)	(0.027)	(0.006)	(0.015)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.003	-0.023*	0.011	-0.013*
	(0.004)	(0.012)	(0.010)	(0.006)
N	41063	5697	21147	14219

Notes: This table shows the estimates of a *static* version of model (3.1) for the probability of unemployment for resident subjects in Switzerland who are active in private manufacturing sectors. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the occurrence of the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Panel A refers to the impact of the shock on the probability of registered unemployment, while panel B refers to its impact on non-registered unemployment. Column (1) does not distinguish between age groups, while Columns (2)-(4) focus on different age groups (18–30; 31–49; 50–64). All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, and a dummy variable for Swiss nationality. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table C.2.8: Resident Workers' Labor Market Outcomes - Manufacturing Sectors (2011-2018)

	(1) Baseline	(2) Only Imports	(3) Only Exports
Panel A: Unemployment			
$\tau_s \times \mathbb{I}[2015, 2016]$	0.009	0.010	0.003
	(0.009)	(0.009)	(0.006)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.000	-0.004	0.011
	(0.005)	(0.003)	(0.014)
N	42212	42212	42212
Panel B: Earnings			
$\tau_s \times \mathbb{I}[2015, 2016]$	-0.027***	-0.032***	0.002
	(0.008)	(0.008)	(0.009)
$\tau_s \times \mathbb{I}[2017, 2018]$	-0.016	-0.015	-0.012
	(0.010)	(0.010)	(0.017)
N	34536	34536	34536

Notes: This table shows the estimates of a *static* version of model (3.1) for the labor market outcomes of resident subjects in Switzerland who are active in private manufacturing sectors. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the occurrence of the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Panel A refers to the impact of the shock on the probability of unemployment, while panel B refers to the impact on the logarithm of real net annual earnings at 2014 prices. Column (1) reports the estimates of the baseline diff-in-diff model, while Columns (2) and (3) report the estimates when the continuous treatment variable is an alternative version of exposure index τ_s that excludes, respectively, exports or imports. Note that columns are not directly comparable, as the use of alternative measures of trade exposure results in slightly different orderings of affected sectors. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at sector and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table C.2.9: Resident Workers' Earnings by Skill Level of Occupation - Service Sectors (2011-2018)

	(1) All	(2) Low-Skilled	(3) High-Skilled
$\phi_\ell \times \mathbb{I}[2015, 2016]$	-0.014**	-0.023**	-0.008
	(0.005)	(0.009)	(0.010)
$\phi_\ell \times \mathbb{I}[2017, 2018]$	-0.003	-0.004	-0.005
	(0.006)	(0.008)	(0.015)
N	119132	60651	58481

Notes: This table shows the estimates of a *static* version of model (3.2) for the logarithm of the real net annual earnings (at 2014 prices) of resident subjects in Switzerland who are active in private service sectors. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the occurrence of the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Column (1) reports the estimates for all workers, while Columns (2) and (3) focus on, respectively, low-skilled and high-skilled occupations (*International Standard Classification of Occupations*). All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, the type of working contract, the number of weekly hours worked, a dummy variable for part-time work, and a dummy variable for high-skilled occupations. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table C.2.10: Resident Workers' Labor Market Outcomes - Service Sectors (2011-2018)

	(1) All	(2) Age 18-30	(3) Age 31-49	(4) Age 50-64
Panel A: Unemployment				
$\phi_\ell \times \mathbb{I}[2015, 2016]$	0.002	-0.006	0.002	0.009*
	(0.004)	(0.010)	(0.006)	(0.004)
$\phi_\ell \times \mathbb{I}[2017, 2018]$	-0.003	-0.010	-0.004	0.005
	(0.004)	(0.011)	(0.005)	(0.007)
N	162543	27388	83603	51550
Panel B: Earnings				
$\phi_\ell \times \mathbb{I}[2015, 2016]$	-0.014**	0.007	-0.022**	-0.024*
	(0.005)	(0.010)	(0.007)	(0.010)
$\phi_\ell \times \mathbb{I}[2017, 2018]$	-0.003	0.029	-0.004	-0.028**
	(0.006)	(0.016)	(0.010)	(0.011)
N	119132	22642	62988	33501

Notes: This table shows the estimates of a *static* version of model (3.2) for the labor market outcomes of resident subjects in Switzerland who are active in private service sectors. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Panel A refers to the impact of the shock on the probability of unemployment, while panel B refers to the logarithm of real net annual earnings at 2014 prices. Column (1) does not distinguish between age groups, while Columns (2)-(4) focus on different age groups (18–30; 31–49; 50–64). All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, a dummy variable for part-time work, and a dummy variable for high-skilled occupations. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

Table C.2.11: Resident Workers' Earnings by Education and Skill Level of Occupation - Service sectors - Age 18–30 (2011-2018)

	(1)	(2)	(3)	(4)
	T. Edu High Occ.	No Edu Low Occ.	T. Edu Low Occ.	No Edu High Occ.
$\phi_\ell \times \mathbb{I}[2015, 2016]$	0.058	-0.022*	-0.005	0.044
	(0.038)	(0.012)	(0.058)	(0.024)
$\phi_\ell \times \mathbb{I}[2017, 2018]$	0.053	0.014	0.003	0.052
	(0.046)	(0.015)	(0.088)	(0.028)
N	4253	11635	1370	5370

Notes: This table shows the estimates of a *static* version of model (3.2) for the logarithm of the real net annual earnings (at 2014 prices) of young (18–30) resident subjects in Switzerland who are active in private service sectors. The dummy variable $\mathbb{I}[2015, 2016]$ takes value one in the two years right after the shock (i.e., 2015 and 2016), while the dummy variable $\mathbb{I}[2017, 2018]$ takes value one in the two subsequent years (i.e., 2017 and 2018). Column (1) refers to young workers with tertiary education in high-skilled occupations, Column (2) refers to young workers without tertiary education in low-skilled occupations, Column (3) refers to young workers with tertiary education but in low-skilled occupations, and Column (4) refers to young workers in high-skilled occupations but without tertiary education. All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for Swiss nationality, a quadratic polynomial for age, the type of working contract, the number of weekly hours worked, and a dummy variable for part-time work. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. Significance levels: *** p < 0.01; ** $0.01 \leq$ p < 0.05; * $0.05 \leq$ p < 0.10.

Table C.2.12: Resident Workers' Labor Market Outcomes - Service Sectors - Triple Difference Estimator (2011–2018)

	(1)	(2)	(3)	(4)
	All	Age 18-30	Age 31-49	Age 50-64
Panel A: Unemployment				
$\phi_\ell \times \mathbb{I}[2015, 2016]$	0.003	-0.009	0.011*	0.003
	(0.005)	(0.013)	(0.005)	(0.006)
$\mathbb{I}[2015, 2016] \times$ border	0.006	-0.035	0.073***	-0.063*
	(0.015)	(0.069)	(0.020)	(0.032)
$\phi_\ell \times \mathbb{I}[2015, 2016] \times$ border	-0.003	0.013	-0.025**	0.017
	(0.003)	(0.021)	(0.008)	(0.010)
$\phi_\ell \times \mathbb{I}[2017, 2018]$	0.003	-0.004	-0.002	0.020*
	(0.006)	(0.016)	(0.006)	(0.010)
$\mathbb{I}[2017, 2018] \times$ border	0.062***	0.072	0.015	0.149**
	(0.017)	(0.099)	(0.026)	(0.058)
$\phi_\ell \times \mathbb{I}[2017, 2018] \times$ border	-0.021***	-0.022	-0.006	-0.049**
	(0.005)	(0.033)	(0.009)	(0.019)
N	162543	27388	83603	51550
Panel B: Earnings				
$\phi_\ell \times \mathbb{I}[2015, 2016]$	-0.011	-0.007	-0.013	-0.014
	(0.007)	(0.011)	(0.009)	(0.015)
$\mathbb{I}[2015, 2016] \times$ border	0.015	-0.167**	0.081	0.056
	(0.048)	(0.062)	(0.044)	(0.090)
$\phi_\ell \times \mathbb{I}[2015, 2016] \times$ border	-0.011	0.047**	-0.029*	-0.030
	(0.015)	(0.020)	(0.014)	(0.030)
$\phi_\ell \times \mathbb{I}[2017, 2018]$	-0.007	0.016	-0.004	-0.035**
	(0.008)	(0.015)	(0.011)	(0.013)
$\mathbb{I}[2017, 2018] \times$ border	-0.047	-0.161	-0.002	-0.057
	(0.041)	(0.106)	(0.052)	(0.070)
$\phi_\ell \times \mathbb{I}[2017, 2018] \times$ border	0.013	0.039	-0.000	0.021
	(0.012)	(0.032)	(0.017)	(0.024)
N	119132	22642	62988	33501

Notes: This table shows the estimates of a *static* version of model (3.2) for the labor market outcomes of resident subjects in Switzerland who are active in private service sectors, accounting also for distance from the border using a triple difference estimator. Border labor market areas are those whose centroid has a distance from the nearest border crossing office of at most 10 kilometers. Panel A refers to the impact of the shock on the probability of unemployment, while panel B refers to the logarithm of real net annual earnings at 2014 prices. Column (1) does not distinguish between age groups, while Columns (2)-(4) focus on different age groups (18–30; 31–49; 50–64). All models include sector, labor market area, and year fixed effects, plus a vector of controls including sex, marital status, number of children, a dummy variable for tertiary education, a dummy variable for Swiss nationality, a quadratic polynomial for age, and – only when wages are the outcome variable – the type of working contract, the number of weekly hours worked, a dummy variable for part-time work, and a dummy variable for high-skilled occupations. Robust standard errors are two-way clustered at labor market area and year level. Estimates are weighted using sample weights. Significance levels: *** $p < 0.01$; ** $0.01 \leq p < 0.05$; * $0.05 \leq p < 0.10$.

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