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ABSTRACT

How Do Firms Adjust to Negative Labor Supply Shocks? Evidence from Migration Outflows*

The quality of workers in a country positively relates to productivity of firms, adoption of new technologies, and growth. This paper studies adjustments of Italian firms to negative labor supply shocks in the context of workers' outflows from Italy to Switzerland. My diff-in-diff leverages the implementation of a policy in which Switzerland granted free labor market mobility to EU citizens and different treatment intensity of Italian firms based on their distance to the Swiss border. Using detailed social security data on the universe of Italian firms and workers, I document large (12 percentage points higher) outflows of workers and fewer (2.5 percentage points) surviving firms in the treatment group relative to control. Despite replacing workers and becoming more capital intensive, treated firms are less productive and pay lower wages. I investigate this evidence through the lens of a simple production function with high and low-skilled labor within a heterogeneity analysis based on the skill intensity of the industry of each firm. In line with the brain drain literature, I show how adverse effects of large outflows of workers operate through firms that workers leave. I provide suggestive evidence that high-skill intensive firms are the main driver of the negative results on wages and productivity. I also show that low skill intensive firms instead suffer less from losing workers and provide new job opportunities for the workers who do not migrate.

JEL Classification: F22, J22, J24, J61

Keywords: migration, labor supply, skills, firms

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1 Introduction

The average quality of workers is a key determinant to productivity and wealth in every nation Lucas (1988) and local shocks to the labor supply may influence the quality of the workforce. The literature on brain drain[1] has studied the consequences of outflows of workers at the country level, documenting positive and negative effects on human capital accumulation and technology adoption. Little is known however, on how effects of large outflows in the labor force operate through firms in the labor market. Following a worldwide increase in the mobility of labor, labor markets adjustments to these shocks have gained attention in the literature. Few papers have looked at the implications of this phenomenon at the firm level, and all of them have focused on an increase in local labor supply, making the labor factor more abundant.[2] While recent papers started studying the consequences of worker's outflows,[3] evidence on firms that lose workers on a large scale is still limited.[4]

In this paper, I provide empirical evidence that, especially in some sectors, losses of workers translate into losses of firm productivity and firm destruction. To do so, I exploit the effects of the complete removal of immigration restrictions between Italy and Switzerland in 2000 on Italian firms and I implement a difference in differences specification. My diff-in-diff leverages the timing of the agreement and the intensity of the treatment based on the distance of the Italian firm to the Swiss border. With the implementation of the EU Agreement on the Free Movement of Persons Italian cross border workers and resident immigrants were granted free access to the Swiss labor market. Using information on the Italian residence of cross border workers and immigrants, I show that Italian municipalities closer to the Swiss border were more exposed to the probability of losing workers to the Swiss firms. The fact that almost 80% of cross border workers lives within 30 minutes of commuting time to the Swiss border motivates my identification strategy.

I use unique, detailed social security data on the universe of Italian workers and firms together with balance sheet data, looking for the first time at granular changes in the workforce within each firm and analyzing changes within firms once these workers emigrate.

I first show that treated Italian firms suffered a negative labor supply shock in which they lost

[1] See Docquier and Rapoport (2012) for a review.

[2] See Grossman, 1982; Card, 1990; Altonji and Card, 1991; Goldin, 1994; Borjas et al., 1997, 1996; Card, 2001; Angrist and Kugler, 2003; Borjas, 1999, 2003; Manacorda et al., 2012; Ottaviano and Peri, 2012; Borjas, 2017; Monras, 2019.

[3] Andersson et al., 2020; Fernandez-Sanchez, 2020; Hafner, 2019; Butikofer et al., 2020.

[4] Jäger (2016) shows how firms substitute for single exits of workers because of their sudden death.Sauvagnat and Schivardi (2019) implement a similar analysis looking at managers. A Theoretical debate on this topic has been developed by Stole and Zwiebel, 1996a,b, and De Fontenay and Gans (2003).

employment to Swiss firms. I document a large outflow of workers from treated Italian firms close to the border between 1994 and 2015. As it is not possible to identify workers who leave Italy and move their job to Switzerland in the Italian data, I study *exits* of workers.[5] I show that while there is no difference in exits before the reform, treated firms lost 12 percentage points more of their employment after free access to the Swiss labor market compared to control firms.

I evaluate the effects of the reform first on firm entry and exit, and then on four margins of adjustment: employment, wages, productivity, and capital accumulation. I find that municipalities closer to the Swiss border have 2 percentage points fewer firms after the reform. Surviving firms, despite replacing workers to keep employment constant and becoming more capital intensive, are less productive and pay lower wages. I investigate this evidence through the lens of a simple production function framework with high and low-skilled labor. I implement a heterogeneity analysis based on the skill intensity of the sector of the firm and provide suggestive evidence that manufacturing and high-skill intensive firms are the main driver of the negative results on wages and productivity through four mechanisms.

First, I show high-skill intensive manufacturing firms have 1.5% lower wages because of a composition and a replacement effect. Lower wages are in fact observed for remaining workers in these firms (composition effect) and also for newly hired ones (replacement effect). The analysis of workers' fixed effects (following Abowd et al. (1999) - AKM) suggests this is likely driven by lack of firm specific human capital when firms replace workers with imperfect substitutes.[6] In line with the standard production framework instead, incumbent workers in low-skill intensive firms have higher wages, and I find no effect on wages of new workers.

Second, I show that a loss of high-skill workers results in higher productivity losses for manufacturing firms. This can follow both from the lower quality of new workers or from a contraction in knowledge spillovers.[7]

Third, I show that firms are more likely to enter industries not experiencing losses of productivity and relying on the most abundant skills left on the market. This translates into fewer firms entering high-skill intensive markets, and more firms entering sectors that rely on low-skilled labor.

Fourth, firms might adopt new technologies which are more productive in the most abundant labor factor. Such a mechanism would imply a higher investment in physical capital to complement

[5] I define *exit* as a worker who disappears from social security data without a pension or a death spell.

[6] Another channel might be that the firm hires workers of lower quality. However, the fact that the average AKM of workers in these firms is higher, suggests that these workers are not per se of lower ability.

[7] See Kerr et al., 2015; Peri et al., 2015b

the most abundant skills on the market. In this respect, I find all firms to become more capital intensive. High and low-skill intensive firms might accumulate more capital to increase productivity of lower skilled workers.

Finally, I find that low skill intensive firms, who suffer less from losing workers, replace the workers they lost providing job opportunities for traditionally disadvantaged categories of workers: the average worker in these firms is now younger, less experienced and more likely to be a woman or an immigrant in Italy.

This paper makes three contributions. First, it contributes to the literature on brain drain showing how adverse effects of large outflows of workers operate through firms that workers leave. The brain drain literature highlights how an outflow of workers can have both negative or positive consequences in terms of productivity and human capital accumulation. Macro and micro evidence so far document the effects of emigration on human capital accumulation overlooking however, the role of firms in this process.[8] The only exception is Giesing and Laurentsyeva (2018) which analyze in a cross-country study the effect of skilled emigration after the EU enlargement. Using aggregate migration data and a panel sample of firms, they find negative short-term effects on regional TFP of firms in the eastern Europe. My results look at workers within firms and document that negative effects of outflows act in the labor market through productivity losses and lower entrance of high-skilled firms. At the same time, I document that losses of low-skilled labor may not have strong negative consequences in the country of origin. If anything, the higher outflows of unskilled workers relates to new labor market opportunities for low-skilled workers who do not migrate. While I cannot advance any claim on welfare effects, my research points out the importance of having thick markets in specific skills, meaning an abundance of workers across different skill levels. It is possible that overall the bordering Italian regions are doing better because the outflow of workers opens up new opportunities for women, young workers, and people with lower labor market experience. On the other hand, if firms who lose are the most skilled, technological and productive ones, the long run effect of the labor market integration in these regions will depend on which of the two effects will prevail.

Second, it contributes to the the immigration literature. The majority of research in this literature focuses on the impact of migration flows on the labor market consequences on firms and native workers in the country of destination (see, e.g., Dustmann and Glitz, 2015; Beerli et al., 2018;

[8]Theoretical work of Wong and Yip (1999) and Haque and Kim (1995) shows that negative consequences on productivity and growth happen when the stock of human capital is exogenous, or when the additional creation of human capital ends up abroad. Kremer (1993) shows this effect can also act through occupational shortages.

Dustmann et al., 2017). This paper investigates these effects on firms in the country of origin of the immigrants. Other works in this respect (see, e.g., Clemens et al., 2018; Andersson et al., 2020; Fernandez-Sanchez, 2020) have focused on historical mass migration and its effects on factors' prices and technology adoption in specific sectors, or on human capital accumulation, but have not been able to address adjustments at the firm level. Hafner (2019) studies the impact of labor market integration between Switzerland and France on French workers finding that low-skilled employees increase their bargaining power and their wages raise.[9] A recent strand of this literature studies the effect of introducing again restrictions to immigration in countries that lifted them in the past.[10] Reintroducing restrictions to immigration or the deportation of immigrants is another mechanism that could cause firms to lose workers.

My third contribution is to the literature on imperfect substitutability, imperfect labor markets, and firms' monopsony power (see, e.g., Jäger, 2016; Manning, 2003, 2011; Hafner, 2019). To the best of my knowledge, this is the first paper showing how firms adjust to large negative labor outflows and not just single workers' deaths, expanding the analysis to the consequences of these losses in terms of firms' performance. I find the same adjustment mechanisms following workers' deaths can explain the behavior of firms when substituting many workers. In particular, my findings suggest that wages are lower when firms replace workers with imperfect substitutes and the effects persist over time, meaning that skills and industry specific human capital matters and cannot be easily acquired by newly hired employees. In addition, I show that becoming more capital intensive does not lead to higher productivity when the firm is lacking fundamental skills. The results on capital speak in favor of endogenous choice of technique or multisector models rather than models with separable capital or capital-skills complementarities.[11] I also highlight a crucial role of labor market tightness in showing that firm response crucially depends on how large is the pool of similar workers from which the firm can substitute for the lost ones. When the pool of workers is large the firm can easily replace the skills lost and retain workers increasing their wages, without incurring into losses of productivity.[12]

The rest of the paper proceeds as follows: Section 2 presents the institutional framework. Section 3 introduces the data. Section 4 discusses empirical strategy and identification. Section 5 presents

[9] Butikofer et al. (2020) study wage effects on Swedish residents after gaining access to the Danish labor market. Exploiting the opening of the Öresund bridge, they find an increase in Swedish wages by 13% within eight years especially for highly educated men.

[10] See East et al., 2018; East and Velasquez, 2018

[11] See Lewis (2013)

[12] A closely related literature is the one on costs of turnover Abowd and Kramarz, 2003; Manning, 2006; Blatter et al., 2012. My findings suggest that turnover might be more costly when the labor market is tight.

my main results. Section 6 discusses the conceptual framework and possible mechanisms presenting evidence supporting these mechanisms. Section 7 discusses my findings within the existing literature. Section 8 concludes.

2 Institutional setting

In this section, I present evidence on the large labor outflows which make the Swiss-Italian migration context an appropriate setting to answer my research question. First, I describe the institutional framework of migration between the Italian and Swiss labor market: I discuss the strong restrictions to obtaining a working permit in Switzerland as a cross border worker or a resident immigrant. Then, I illustrate how these restrictions were removed from 2000. Finally, I use Swiss social security data to show descriptive evidence on the outflows of Italian workers to Switzerland. I describe how I use this evidence to motivate my identification.

2.1 Italian and Swiss labor markets

In the following, I show why the Swiss labor market is attractive to Italian workers, and I explain the strong restrictions EU workers had to face to work in Switzerland before 2000.

Italy and Switzerland are two of the most rich economies in the world[13] and geographical proximity makes the Swiss and Italian labor market strongly connected, yet these labor markets differ along many dimensions. Figure 1 provides a map of Italy and Switzerland. Three Swiss cantons share borders with four Italian regions and six Italian provinces. The Italian bordering provinces have a labor force of almost 800'000 people and represent one of the most productive Italian areas. The bordering cantons instead, had a labor force of around 350'000 people in 1998. This number increased up to almost one million people in 2015, and one out of three workers is now a foreigner. The average wage in the bordering Swiss cantons is around 4'500 Swiss Francs (roughly 4'200 Euros). The average wage in the bordering Italian provinces is instead of 1'800 Euros.[14] The unemployment rate in Switzerland ranged between 2% and 6% in the last 20 years, while the Italian one between 4% and 8%. The relatively small dimension of the Swiss labor market has made Swiss firms active in recruiting more skills and labor from abroad. At the same time, high Swiss wages

[13] Italy is the 8th country by GDP and Switzerland ranks at the 20th place. In terms of GDP per capita, Switzerland is the second richest country in the world, while Italy is number 26th.

[14] Wages are in real terms and gross of taxes and social contributions which are lower in Switzerland, providing an underestimation of the wage gap. Wage differentials are even more pronounced for workers in a managerial, professional, or technical occupation. High-skilled occupations in Switzerland pay on average 6'200 CHF per month (slightly fewer than 6'000 EUR). The same occupations pay in Italy 2'200 EUR on average.

have made Swiss firms very attractive to foreign workers[15]. Italian immigration to Switzerland is a phenomenon which has been growing for longer than a century, and Italian regions bordering with Switzerland have always been particularly exposed to this phenomenon.[16]

Until 1999 it was hard to obtain a permit as a resident immigrant or as a cross border worker, which are the two most common type of permits nowadays.[17] Both resident immigrants and cross borders were subject to yearly quotas. The duration of a cross border permit was limited to one year and tied to a specific job in a bordering Swiss canton. Also, cross border workers were required to commute every day back to Italy and to have lived close to the border for at least six months before applying for the permit. Finally, Swiss employers had to search for six months for a suitable resident worker before hiring a cross border, the so called "priority requirement". The strict regulations were in place until Switzerland signed a new agreement with the European Union in 1999.

2.2 Agreement on the Free Movement of Persons in 1999

I now describe how the ratification of the Agreement on the Free Movement of Persons between Switzerland and the EU brought a large drop in restrictions to working in Switzerland generating a huge flow of Italian workers to Switzerland. In 1998 the Swiss federal government announced the implementation of several agreements with the European Union. The most important was the Agreement on the Free Movement of Persons which completely changed the previous rules about immigration.[18] After ratification in 1999, and passing a referendum in 2000, all restrictions where gradually removed from 2002. The labor market for cross border workers was fully liberalized in 2004 with the abolition of the priority requirement. Restrictions for resident immigrants have been fully lifted in 2007. In 2008 Switzerland also joined the Schengen area and removed controls on persons at the border. It is unlikely that local economic conditions in Switzerland were a consideration in the timing and content of the reform.[19] A deeper discussion of the reform process, and about the effects of the other agreements signed between the EU and Switzerland is available in Appendix C.1.

[15] Especially wages of cross-border workers have a higher purchasing power as these workers live abroad and suffer less from higher prices in Switzerland.

[16] After World War II Italians represented a very cheep and large pool of workers for the Swiss firms, and Italy and Switzerland set very strict regulations to allow Italian citizens to work in Switzerland since the 1950s. A new regulation was implemented in the 1970.

[17] Until the mid 90s Italians working in Switzerland were mostly seasonal workers.

[18] Other agreements regulated reductions in trade costs, an had the general purpose of increasing competition between Switzerland and the EU. Table 19 reports an overview of all agreements.

[19] See Beerli et al. (2018).

2.3 Descriptive evidence on Italians in Switzerland

I now briefly describe Swiss social security data and then present descriptive evidence on the volume of flows from Italy to Switzerland. Exploiting information on the Italian residence of cross border workers and immigrants, I show bordering Italian regions are more exposed to the probability of losing workers to the Swiss firms. I then exploit this information to motivate my difference in differences specification.

I rely on information from the Swiss social security dataset provided by the Swiss Statistical Office. I mostly rely on ZEMIS, a dataset containing employment spells of immigrants working in Switzerland. I exploit the nationality of immigrants and their resident permit. I can distinguish between resident immigrants and cross border workers. Italian regions bordering with Switzerland are more exposed to immigration because because workers living closer to the border have a lower cost to move their job to Switzerland. The lower commuting cost applies both to resident immigrants and to cross border workers, who can work in Switzerland while living in Italy. Cross borders can reach the new employer within a short commuting time, they do not face any language barrier[20], and they get offered a salary that is on average three times higher than the one they are offered in Italy.

Cross border working is the major form of migration in bordering regions, and builds up to almost one third of total Italian working migration to Switzerland. For cross borders I observe the municipality of residence in Italy and rely on this information to motivate my identification design.[21] I also build a dataset of distances computing the driving time, driving kilometers, and air distance to the closest Swiss-Italian border crossing for each municipality in the bordering Italian regions.[22]

My analysis and identification rely on the exposure of Italian municipalities to the phenomenon of cross border workers as almost 80% of them lives within 30 minutes from the border.[23] Figure 2 shows the effect of the reform on the inflow of Italian workers in Switzerland. Panel A shows the stock of Italian cross border workers in Switzerland. This number increased from from 20'000 in 1990 to almost 80'000 in 2015. The yearly inflow of cross borders raised from around 4'000

[20] All bordering cantons have Italian as one of their official languages

[21] For residence immigrants I rely on aggregated municipality-level information on the last residence of Italian immigrants from the register foreign residents.

[22] Technically, I compute these distances for all the municipalities within the same distance of the farthest municipality in a bordering province.

[23] Table 21. As they commute regularly to Switzerland, cross borders live close to the border by definition. Resident immigrants are instead widespread across Italy. An extensive discussion about resident immigrants can be found in the appendix D.

new Italian workers in Switzerland to around 15'000 new workers per year.[24] The number of Swiss citizens working in Italy is much lower. The total number of Swiss citizens working in the bordering regions of Italy is between 4'000 and 5'000 per year.[25]

Panel B of figure 2 shows that the Swiss labor market became relatively more attractive for high-skilled workers. The graph plots the share of cross borders in high skilled occupations.[26] High skilled workers represented 10% of cross borders in 1990. Today they are more than 30% of the total, roughly 25'000. The number of low skilled cross borders increased four times during the sample period, while the number of high skilled workers is almost ten times higher than it was in 1990.[27] Table 21 in appendix D reports detailed summary characteristics for Italian workers in Switzerland. The average Italian working in Switzerland is around 45 years old. Cross borders are younger with an average age of 39 years. Almost 40% of these workers are women and have been employed in Switzerland for 14 years. One fifth of cross borders has a high skilled occupation and 28% of them works in a high skill intensive firm. Cross borders have fewer than two working spells each and their average wages are around 4'200 Swiss Francs. 92% of cross borders works in Ticino and 7% of them in other bordering cantons. The remaining 1% works in other non-bordering Swiss cantons. The average cross border commutes 25 minutes to reach the Swiss border.

The share of expat (cross border and residents) workers decreases with the distance from the border. Figure 3 shows this pattern ranking Italian municipalities on the horizontal axis into 5 minutes bins of driving distance to the Swiss border. The vertical axis shows the number of expat workers as a share of 1991 population in these municipalities. Each line is for a different year from 1994 to 2007.[28]

The municipalities closer to the border have a higher share of expat workers already in 1994. This number increases over time and the line becomes steeper in the closest municipalities. By 2007 between 3% and 15% of the 1991 population in municipalities within 15 minutes had a job in Switzerland. In municipalities between 15 and 30 minutes to the border expat workers represent at most 3% of the population. Finally, the share of expat workers in municipalities over 30 minutes of commuting time to the border is close to zero percent.[29]

[24] The total number of Italians working in Switzerland increased from 140'000 in 1990 to more than 315'000 in 2015. Cross borders represent one third of the total Italian workforce in Switzerland.

[25] The yearly inflow of new Swiss workers goes actually down from 283 in 1994 to 106 in 2015. In the Italian data I observe 15 Swiss citizens explicitly registered as cross borders working in the Italian bordering regions.

[26] High skilled occupations are ISCO codes 1,2, and 3.

[27] All these figures are available in Appendix D.

[28] The lines stop in 2007 as I miss information on the municipality of residence of cross border workers after 2007.

[29] I cannot build the same figure using labor force instead of population because residence, in the Italian data, is not time variant. When I measure cross borders as share of the labor force in 2017 (the only year for which residence

The same figure 3 allows me to divide Italian municipalities into three regions of exposure to the phenomenon of expat workers (especially cross borders). The share of expats in municipalities within 15 minutes is indeed significantly high already before 1999 and increases over time ranging between 4% and 14% of the whole population in these cities. In municipalities between 15 and 30 minutes from the border, expat workers represent between 1% and 4% of the population. The share of expat workers in municipalities further away than 30 minutes from the Swiss border is zero. I therefore define municipalities in a 0-15 minutes bin of commuting time to the Swiss border as treated, municipalities in a 15-30 minutes bin of commuting time as moderately treated, and municipalities with more than 30 minutes as control municipalities. Under the assumption that workers live close to where they work, I can translate this setting to allocate firms across the same treatment groups as I illustrate in the next section.

3 Data and definition of workers' exits

I now describe the Italian social security and firm data which I use for my analysis. As I cannot explicitly identify workers who move to Switzerland, I define *exits* as workers who disappear from Italian social security data and I explain why I use *exits* to proxy for workers who left Italy to work in Switzerland.

3.1 Italian data

Italian social security data are provided by INPS, the Italian National Institute of Social Security through the VisitINPS program.[30] INPS provides matched employer-employee data from 1983 to 2018. The datasets cover contribution histories of individual workers for the universe of Italian employees in the private sector. Employers directly provide the institute with information about their employees when paying mandatory contributions of their workers. I observe complete employment histories of workers and every contract of a worker within a year. For each employer-employee record I have yearly information on gross monthly earnings, weeks worked, months in which the worker was employed, start date of contract, end date and reason for termination, full-time or part-time employment. In the latter case I observe the share of part-time employment which I use to build

information is reliable, I find that cross borders are 30 to 60% of the Italian labor force in treated municipalities. The same number is around 10% in moderately treated municipalities, and again zero for municipalities in the control group.

[30] Access to the data was provided through the VisitINPS Scholar B program.

full-time-equivalent employment measures.[31] The main measure of income are yearly wages which I deflate to the 2015 CPI.[32] Employment is measured in weeks. Weeks are the actual number of weeks *paid* to each employee.[33] Using the number of weeks worked within a year I construct weekly wages. One limitation of the data is that occupation is not available. I am able however, to vertically classify occupations according to managerial, white collar, blue collar, or apprentice status. Another limitation is that information about education is only available for workers who started a new employment relationship after 2010. For each worker I have a rich set of demographics: year and month of birth, gender, most recent municipality of residence, and nationality. For each worker I also observe the date of old age pension and death.

In the firm data, I observe the complete universe of private sector firms with their demographics. The unit of observation is an establishment, but the dataset also reports the *id* of the firm.[34] I have information on sector, legal type of company, location, entry date, and exit date. The datasets cover around 80% of Italian employment and the excluded categories are self-employed workers, workers in the public administration, and workers in the agricultural sector.[35]

Balance sheets data I complement the INPS firm information with balance sheet's data provided by *Cerved*, the Italian leg of *Aida*, also through the VisitINPS program. Cerved data are available from 1996 to 2016 featuring the universe of incorporated firms.[36] Firms in these dataset account for 70% of manufacturing value added from national accounts.[37] I rely on information on profits, revenues, value added, cost of labor, and the book value of tangible and intangible assets for fixed capital. Cerved data are only available at the *firm* level. I therefore restrict the sample to single establishment firms when using them. A more detailed exposition of the data is available in appendix

[31] The following variables are available form 2005: exact end date of contract, reason for termination, municipality of work.

[32] Income is the sum of two variables: *imponibile* which is the amount of wage subjected to social security contributions, and extra payments not subjected to social security contributions.

[33] For example consider two workers who are employed for one month. The first worker is employed at 100% and the second one at 50%. I observe four weeks paid for the former and two weeks for the latter employee.

[34] For example, a firm who operates a mill and a bakery, or a gasoline station and a shop would appear as two establishments and a single firm. Establishments might have different "plants". For example a bakery with two shops in two different towns of the same province would appear as a single establishment. "Plants" are possible to identify only after 2005, exploiting the combination of establishment *id* and workplace of its workforce. As this information does not cover my whole sample period, my unit of analysis is an establishment. After 2005 I observe 35% of establishments with multiple plants. Instead, the average number of establishments per firm is 1.07 (Istat, Census 2011 data).

[35] Two datasets are available with a sample of self-employed workers, and workers related to other pension funds such as public sector employees. I use these dataset to correct my measure of exit, and to control for absence of trends across the treatment groups. The only type of employment where I have no information is for workers in the agricultural sector.

[36] They are available for roughly 20% of my sample.

[37] Calligaris et al. (2018).

C.2. I also use for further robustness analysis INVIND data.[38]

Workers' exits I am not able to explicitly identify workers who move to Switzerland. For this reason I define *exits*. An *exit* is a worker who completely disappear from social security data without a death or a pension spell. The idea is that when a worker leaves the Italian labor market he stops paying social security contributions and disappears from the data. I therefore expect to observe higher exits in firms geographically closer to Switzerland after the liberalization of the labor market. I do not flag exits of workers from which I observe a pension spell to avoid including workers in early retirement, and workers who leave to Switzerland close to the pension age.[39]. In the analysis I rely on full time equivalent exits as a comparable measure of loss in the workforce between different firms.

3.2 Sample Selection

I illustrate now how I select my final sample of firms and present summary statistics for Italian firms in the three treatment groups. To build my working sample from the original dataset I first keep all workers aged between 16 and 65 who have at least one employment spell between 1994 and 2015. I construct Full Time Equivalent employment using the share of part time work and I restrict the sample to firms who have between 3 and 250 full time equivalent employees within one year.[40] Firms of this size represent roughly 42% of Italian employment. I keep only firms within 75 minutes from the Swiss border.[41] I exclude firms in Milan because of its mobile labor market, being an outlier with respect to exits with more than 80'000 workers disappearing from social security data

[38] INVIND is the annual survey on manufacturing and service firms conducted at the Bank of Italy. Surveyed firms have at least 20 employees. Given the size limit, and the specificity of my treated labor market, very few firms from this survey match with my sample. Evidence produced with this data should be taken as purely suggestive.

[39] I also correct my exit measure anytime I observe a later spell in the sample of self-employment or of other pension funds. Other pension funds include contributions of public employees, retailers, workers in the movie, art, or music industry, and external collaborators. Technically, observing a worker in one of these datasets after an exit does not exclude the possibility that this worker moved his job to Switzerland and is now registered in Italy as self-employed or as an external collaborator. In addition, *exits* do not include returning migration. My measure of *exit* is therefore a rather conservative one.

[40] Firms larger than 250 employees are fewer than 0.03% of all Italian firms. They are excluded as they have multiple plants and are harder to locate within one municipality. Firms smaller than 3 FTE employees are excluded to avoid concerns of mechanical negative correlation between their initial size and subsequent growth (see Mata (1994)). Ruffner and Siegenthaler (2017) contains an extended discussion of this issue and regressions using FTE employment in levels rather than logs as dependent variable including these establishments with fewer than three FTEs, as the mechanical correlation is less pronounced in levels.

[41] I exclude firms further away than 75 minutes as the control group is already more than two times large than the two treatment groups together. Also, this is due to size and memory limitations on the server at INPS.

over 10 years.[42] I exclude firms in the public and primary sector, and international organization.[43] I deflate wages to 2015 CPI prices and winsorize them at the 0.5 and 99.5 percentile. I measure earnings both as annual income and weekly wages accounting for the FTE number of weeks worked. For the main analysis, I keep only firms already active in 1998 to eliminate any bias from self selection in firm entry or exit. Table 20 in the appendix compares my final sample to the rest of Italian medium-sized firms in 1998. My sample includes 6.5% of Italian firms which account for 3.6% of Italian employment.[44] The average Italian firm has 10.6 FTE employees, while the average firm in my sample has 14.3 FTE employees. Firms in my final sample hire 3.6 new employees per year in line with the Italian average. They have a lower share of part-time workers, and a similar share of blue collar workers. The average firm in my sample has been active for 13 years (longer than the national average). Italy has a relatively high share of Manufacturing at 20% of value added (OECD 15%, US 16.4%). Firms in manufacturing represents 48% of the final sample.

Summary statistics I describe average characteristics of firms in the pre-treatment period and discuss pre-existing differences of firms across the three groups. Table 2 provides summary statistics for firms in different treatment groups before 1998, the year when the reform was announced. Even though the difference in differences relies on the parallel trends assumption, it is worth showing some descriptive information to asses to what extent the two samples are similar in the pre period. It also provides the baseline to interpret the magnitude of the effects. Columns 1 to 3 report summary statistics for control, moderately treated (15-30 min), and treated (0-15 min) firms. The last two columns report magnitude and significance of the differences between the treatment and control group. My sample consist of 55'161 firms active in 1998. 2'964 firms belong to the treatment group, 9'487 firms belong to the moderate treatment group, and 42'710 firms are in the control group.[45]

Treated firms in the 0-15 minutes bin have a significantly higher share of exits in pre-treatment. On average, they have a .5 percentage points higher share of exits. The difference is quite small, but precisely estimated. This points to the fact that firms closer to Switzerland started losing workers to Swiss firms in the pre-treatment phase already. Treated firms also have a small 1.5 percentage points higher share of hiring and a 1.7 percentage points higher share of separations in

[42] Table 26 shows that my main results do not change when including firms in Milan. Figure 20 ad table 22 show the placebo exercise is less robust when firms in Milan are included.

[43] See Appendix C.2 for a detailed overview of sample selection and variables' construction.

[44] These firms are located in one of the most productive areas of Italy and within provinces with the highest per capita GDP in the country.

[45] The final panel consist of 842'421 firm-year observations while the workers' panel has roughly 13'289'674 observations

the pre-period. Treated firms have 1.8 fewer full time equivalent employees compared to control firms, they pay lower weekly wages in the order of 32 euros, and have 2 weeks less of work per year. 50% of treated firms are in manufacturing compared to 61% in the control group. There is no significant difference in terms of manufacturing and value added between treated and control firms. Treated firms employ a small higher share of women and foreigners, fewer blue collars, and more part time employees. Balance sheets data are available for 23% of firms in the control group and 16% of treated firms. The average firm in the 15 minutes bin (Treated) is 12.6 minutes away from the Swiss border. The average firm in the 15-30 minutes bin (Moderately Treated) is 24.7 minutes away from the Swiss border. The average control firm is 47 minutes away from the border.

4 Empirical strategy and identification

To assess the impact of migration outflows from Italy to Switzerland on Italian firms I implement a DiD specification. To divide firms into treatment and control groups, I rely on different treatment intensity based on the distance of each Italian firm to the Swiss border. I then leverage on exogenous variation from the timing of implementation of the policy on the free movement of people. In the first part of this section, I describe the allocation of firms to treatment and control groups and the treatment periods. I then present regression specifications that I use to study my research question, and discuss identification assumptions and potential threats to identification. Finally, I discuss sample selection and provide summary statistics on Italian firms.

4.1 Assignment to treatment and timing of the reform

I divide firms into two treatment and one control group based on the driving time from the municipality of the firm to the nearest border crossing to Switzerland. Treated firms are located in a bin of 0-15 minutes to the border. Moderately treated firms are located in a 15-30 minutes bin to the border. Firms in the control group are further away than 30 minutes. Figure 4 shows my treatment groups on the map of the Swiss-Italian border.

The main idea is that Italian firms closer to the border are more likely to lose workers to Swiss firms. This is because workers live close to the firm where they work and workers living closer to the border have a lower cost to move their job to Switzerland. The lower commuting cost applies especially to cross border workers who can work in Switzerland while living in Italy. People living within 15 minutes to the border have a very low cost of leaving their job and move to a Swiss firm:

they can reach the new employer within a short commuting time, they do not face any language barrier, and they get offered a salary that is on average three times higher than the one they are offered in Italy.[46]

Table 1: Timeline of Labor Market Integration

Year	1994	1998	**1999**	2002	2003	**2004**	2007	2008	2015
Phase	**Pre-Reform**		**Transition**			**Free Access**			
Effect	Full Restrictions		Less Restrictions			Free CBW		No restrictions	

The time periods of my diff-in-diff follow the implementation of the agreement on the free movement of persons. The policy reform was announced in 1998 and signed in 1999. I define years from 1994 to 1998 as pre-treatment phase. The reform was enacted in 2002 and the full liberalization for Cross Borders happened in 2004. To take into account possible anticipation effects I define a transition phase from 1999 to 2003. Years after 2004 are part of the free access phase which is my treatment period. Table 1 provides a visual overview of the time line of the treatment.

4.2 Equations and identification

Below I present my main DiD specification and an event study framework to isolate the effects of the reform within each year.

I estimate the effect of labor market integration regressing outcome $y_{j,t}$ of firm j at time t on treatment dummies $ST_j = I(d_j < 15)$ and $MT_j = I(15 < d_j < 30)$ where d_j is the distance of firm j to the border. $I(\text{Transition}_t)$ is an indicator for the transition phase (i.e. $\text{Transition}_t = I(1999 \leq t < 2004)$), while $I(\text{Free}_t)$ is an indicator for the free access phase (i.e. $\text{Free} = I(t \geq 2004)$).[47]

$$\begin{aligned} y_{j,t} =& \beta_0^{Tr}[I(d_j < 15) \times I(\text{Transition}_t)] + \delta_0^{Tr}[I(15 < d_j < 30) \times I(\text{Transition}_t)] \\ &+ \beta_1^{F}[I(d_j < 15) \times I(\text{Free}_t))] + \delta_1^{F}[I(15 < d_j < 30) \times I(\text{Free}_t)] \\ &+ \alpha_j + \alpha_t + \gamma X'_{j,t} + \epsilon_{j,t} \end{aligned} \tag{1}$$

[46] As an alternative definition of treatment and control groups, I allocate the firm in the municipality of residence of the median worker. As municipality is not time-variant in the Italian data, I use this as a robustness of my results.

[47] All of my regressions are at the establishment instead of plant level, because job location is available in the data from 2005 only. In case of multi-plant firms, the location of the firm is the location of the headquarter.

I also include time fixed effects α_t and firm α_j fixed effects. $\gamma X'_{j,t}$ includes time varying controls such as province specific trends[48] and a Bartik control for shifts of industry composition at the local labor market level. Coefficients of interest are β_0^{Tr}, δ_0^{Tr}, β_1^F, and δ_1^F. The first two capture the short run effect of labor market integration on treated and moderately treated firms. The last two capture the long run effect of labor market integration in the same groups.[49]

For robustness and graphical representation, I generalize this setting in an event study framework in order to isolate the effects of each year t. According to equation (2) I regress outcome $y_{j,t}$ in firm j and year t on time α_t and firm α_j fixed effects, together with year dummies interacted with indicators for firms in the *Treated* $= I(d_j \leq 15)$ or *Moderately Treated* $= I(15 < d_j \leq 30)$ group.

$$\begin{aligned} y_{j,t} = \alpha_j + \alpha_t + &\sum_{t=1994}^{2018} \beta_{1,t} I(year = t) \times I(d_j < 15) \\ &+ \sum_{t=1994}^{2018} \delta_{1,t} I(year = t) \times I(15 < d_j < 30) + \gamma X'_{j,t} + \epsilon_{j,t} \end{aligned} \tag{2}$$

In the event study $\beta_{1,t}$ and $\delta_{1,t}$ capture the effect for treated firms in each single year.[50] I cluster standard errors at the local labor market level. The model allows for different averages in the three groups which are absorbed by the fixed effects. I do not assume the three groups would have the same average outcomes, rather I assume the outcomes would have developed on parallel trends absent the reform. All the variation for identification comes from variations between firms within the same province who are assigned to different treatment groups.

Identification assumptions and threats to identification. I now illustrate the assumptions underlying my identification and discuss potential threats to identification and how I address them. In order for equation 1 to capture the causal effect of labor market integration one needs the basic assumption of the diff-in-diff to hold: treated firms would have trended similarly to control firms in the absence of labor mobility. While one cannot test this assumption, the event study specification allows to look at pre-trends before the implementation of the reform. Absence of pre-trends can provide a test for the parallel trends assumption. As the definition of the treatment group is based on the distance from the border, one might worry that some endogenous characteristic correlated

[48] Figure 4 shows the granularity of these trends plotting provinces on the map.
[49] Model 1 assumes equal time effects across the three groups of firms. Running the same model with pairs of these three groups does not change my results.
[50] 1997 is used as baseline year.

to being close to the border and to the timing of the reform might affect the outcome itself. In that case, the effect of the labor market integration would be biased. If for example workers in municipalities close to the border are more likely to leave Italy, this effect would positively bias the effect of the reform. Also, there might be region or industry specific endogenous shocks to local demand, prices, or productivity. To control for that, I add trends at the NUTS III level netting out, at a very granular level, any province level trend over time.[51] Also, I build a Bartik control variable in the spirit of Beerli et al. (2018). I therefore control for any nationwide variation in industry composition which might affect industries in my treatment groups. As a final robustness, I replicate my results while assigning the location of the firm to the residence of the median worker [52]. This is to rule out concerns about multiple plant establishments which might be misallocated. Another concern might be internal mobility of workers. If these movements are systematically related to the effects of the reform they might bias my results. I limit these concerns in two ways. First, I check for internal mobility of workers across the three groups. As figure 21 shows, workers always transition to firms closer to the border, separating from firms in the control group. My estimate would then capture the effects of interest at their lower bound. This is consistent with the fact that all groups are exposed to treatment as identification leverages on the fact that treated firms are much strongly affected.[53] Second, I run a placebo estimate where I divide the control group into a placebo treatment group (from 30 to 45 minutes) and a placebo control (from 46 to 75 minutes). One limitation is that workers who work in Switzerland and live in Italy are much richer than before. This could generate positive demand effects on local nontradable industries. I cannot isolate these effects which would be captured in my estimates. Two final concerns are about whether former barriers where forcing Italian firms trading with Swiss firms to be located on the Italian side of the border as well as the implementation of other reforms at the same time of the Agreement on the free movement of persons. First, there is anecdotal evidence of a very small number of firms reallocating to Switzerland. Second, it in not clear how big this relocation incentive could be as it is hard to estimate costs of relocation against labor costs. In this respect

[51] Provinces are displayed in figure 4.

[52] Workers are ranked according to the distance from their municipality of residence to the Swiss border

[53] Workers who leave a firm in the control group and move to one in the treatment groups are around 0.03% of the total number of workers employed in control firms. *Exits* on the other hand might suffer from an upward bias. This happens if workers systematically move from a control to a treated firm with the idea of then finding a job in Switzerland. This is unlikely as a worker would need to leave a job, and find another job in a treated region, with some risk of unemployment or finding a worse match. My estimates of exits are already conservative as I exclude returning migration and I do not label as *exit* workers who become self employed or external collaborators, which actually does not rule out the possibility for them to be employed in Switzerland while being self-employed in Italy or collaborating externally with an Italian firm.

the MRA agreement reduced trade costs and might affect differently these firms closer to the border confounding my results. The reduction of trade costs however, targeted a specific set of industries (such as machinery, medical devices, electrical equipment, construction products, lifts). I can therefore exclude industries directly affected from this agreement and check consistency of the results.[54] I asses the robustness of my results to these threats in Appendix E.

5 Main Results

In this section I first document that the inflow of workers to Switzerland translates into an important labor supply shock for Italian firms at the border. I show these workers belong to every quartile of the wage distribution. I then show that employment losses happen on the extensive margin: treated regions have fewer firms after the reform. Finally, I show that surviving Italian firms replace workers to keep employment constant and become more capital intensive, yet they pay lower wages and become less productive.

5.1 Exits of workers

Figure 5 studies the effect of labor market integration on the loss of employment for firms within 15 minutes to the border (treated) and between 15 and 30 minutes (moderately treated). Figure 5 supports the idea that Italian firms lost workers to the Swiss firms. The graph plots coefficients estimates of $\beta_{j,t}$ (circles) for treated firms ($I[d_j \leq 15]$) and $\delta_{j,t}$ (triangles) for moderately treated firms ($I[15 < d_j \leq 30]$) with 95% confidence intervals according to equation 2. The dependent variable is the yearly flows of exits as share of total employment in 1998. For both treatments, the figure validates the assumption of parallel trends, as estimates before 1998 are not significantly different from the control group. There is no significant difference in flows of exits with the control group. Flows of exits increase right after 1998 and are significantly higher after years when restrictions to mobility where eliminated.[55] Figure 6 shows the effect on the stock of exits as share of the labor force of the firm in 1998.[56] The point estimate becomes significantly positive after 1999 for both groups and keeps increasing over time. In 15 years treated firms have lost 12 percentage points

[54] Ariu (2020) studies the effects of the same labor mobility on exports of Swiss firms. He finds that mobility leads to higher quality products through an upgrading of the quality of inputs from the origin country of the migrants because of more intense relationships with already existing sellers. He does not find an effect on the quantity of input or of increase in exports to the country of origin of the migrants.

[55] Estimates on flows of exits jump up after 2000 when the reform passed the referendum, after 2004, when the labor mobility for cross border workers was fully implemented, and in 2007 when the labor market was liberalized for resident immigrants. They also jump after 2011, when Italy faced the sovereign debt crisis.

[56] The stock of exit is the cumulative of yearly flows of exits from 1998.

more of their labor force in workers' exits.[57] This is almost twice as large as the number of exits in the control group. The effect is smaller in magnitude, around 5 percentage points for moderately treated firms.[58]

Column 1 of table 3 reports the results according to the standard diff-in-diff in specification 1. The average effect in the free access period is a 8.4 percentage points higher exit rate in 0-15 min firms, and a 2.5 percentage points higher exit rate for firms in the 15-30 min bin. Given the baseline of exits in the control group, treated firms lost 1.7 times more workers, and moderately treated ones 47% more workers in exits.[59]

Column 2 to 4 of table 3 decompose exits by quartile of residualized income distribution.[60] The workers who exit are located in all four quartiles of the wage distribution. For treated firms each quartile represents around 2 percentage points of the total estimate of 8 percentage points. Firms in the 15-30 minutes bin do not lose significantly more workers from the top quartile of the wage distribution, and half of worker' exit consist of lower wage workers from the bottom quartile of the wage distribution. These results show that labor market integration between Italy and Switzerland caused Italian workers to leave their firm, and these firms lost 12 percentage points of their original employment to Swiss firms. Next, I show how Italian firms respond to this loss of employment. First, I show evidence on exits of firms and firm creation. Then, I show adjustments of surviving firms with respect to employment, capital accumulation, productivity and wages.

5.2 Fewer firms in treated regions

Following the outflow of workers, I first document that employment opportunities decrease in the bordering regions because of less firms staying on the market. Column 1 of table 4 shows the effect of labor market integration on firm creation at the municipality level according to equation 1.[61] The dependent variable is net entry of firms[62] over total number of firms in a municipality in 1998. Estimates show a net decrease in the number of firms in both municipalities within 15 minutes, and in the 15-30 minutes bin. Estimates are significant for the transition period only. The

[57] Worker's turnover is instead double in treated firms, supporting that my measure of *exits* is quite conservative.

[58] Figure 22 in appendix E shows the raw means.

[59] Table 22 in the appendix reports robustness of equation 1 to the inclusion of fixed effects, NUTS III trends, and a Bartik control for nationwide shifts in employment. Additional panels in Figure 19 show the pattern in Figure 6 is robust to inclusion of several controls, to excluding industries affected by other agreements, and to the subset of firms with balance sheet data.

[60] I residualize log real weekly wages for age, gender, and year fixed effects and allocate each worker to one quartile of the distribution. Figure 13 shows the results graphically.

[61] Figure 14 in Appendix B plots coefficients of interest with 95% CI.

[62] Net entry is defined as total number of firms entering the market in a given year, minus total number of firms exiting the market in the same year. Net entry is then cumulated over the sample period.

point estimates indicate that treated municipalities lost 2-2.5 percentage points of the firms they had in 1998. This means an average of 260 Italian firms[63] disappeared or did not enter the market because of labor market integration. Columns 2 and 3 of table 4 decompose this effect into exit and entry of firms. None of the exit of entry result is significant by itself. This suggest that the overall effect is a composition of higher exits and fewer firms entering the market.

5.3 Adjustments of surviving firms

While the bordering regions lose employment because of fewer firms active on the market, I show that surviving firms keep employment constant and accumulate more capital, they have however a lower productivity and pay lower wages.[64] Table 5 shows the effects on these margins.[65] All surviving firms, both in the 15 minutes and 15-30 minutes bin, manage to keep employment constant. The point estimates are small (in the order of 1%), negative, and not statistically different from zero. This suggests that treated firms manage to replace the workers they lose. This result is confirmed looking at the number of hiring as separations in these firms as share of employment in 1998.[66] Column 2 shows the effect on average log weekly wages at the firm. Here the treatment is still at the firm level, but the observations are at the level of single workers within each firm. According to column (2) average log wages of workers of firms in the 0-15 minutes bin are 1.4% lower in comparison to the control group. Average log wages of workers of firms in the 15-30 minutes bin are instead 7% higher compared to the control group.[67]

Column 3, column 4, and column 5 show the effects on value added per worker, total value added

[63] Approximately 3300 job positions

[64] These main results are estimated on the sample of surviving firms. While attrition of firms leaving the sample might bias my results, it is worth thinking about the direction of the possible bias. In terms of potential outcomes firms that survive after the reform despite being close to the border must be special in some other way; they must be positively selected. Firms that survive away from the border are selected too. If they are selected in the same way of surviving firms closer to the border the sigh of the bias would go against my estimations, which could be therefore considered quite conservative. If firms away from the border are selected in a different way instead and this selection is on trends, results might be biased. This would be the case if, responding to labor market integration, surviving firms close to the border are positive selected while firms away from the border are for some reason negatively selected.

[65] Table 24 in Appendix B replicates this table including only *Cerved* firms for which balance sheet information is available. Results have similar magnitude and direction as in the full sample. Figure 15 also in Appendix B plots coefficients of interest with 95% CI for the free access phase. Figure 23 in appendix E shows the event studies on the main outcomes.

[66] To limit concerns on the use of log employment, table 23 in appendix E reports the number of hiring, separations, and exits as share of employment in 1998.

[67] Table 8 in Appendix B reports results on log average weekly wages at the firm according to regression 1 decomposing the effect between wages of incumbents and wages of newly hired workers. Column (1) reports estimates of column (2) from table 5. This table shows that lower wages in treated firms (0-15 min) are mostly driven by lower wages of newly hired workers. Higher wages in moderately treated firms (15-30 min) are instead driven by higher wages paid to incumbent workers.

and Total Factor Productivity.[68] While firms in the 15-30 minutes bin do not suffer significant productivity losses, firms in the 15 minutes bin lose around 7.5% in terms of value added per worker and total value added in the free labor market phase. In terms of TFP, treated firms lose 9.5%.

Column 6 shows that both firms within 0-15 minutes and firms in the 15-30 minutes bin invest more in assets. The dependent variable is log value of total (tangible and intangible) assets per employee. In the free access phase, firms close to the border increase the value of their assets by 6.8%. The same happens to firms in the 15-30 minutes bin who increase their amount of assets by 6.9%.

Even if firms are able to replace workers and to invest in assets, they suffer from lower productivity and pay lower wages. In a standard production framework an outflow of workers, when nothing else changes, would result in higher wages at the firm. A possible mechanism could be that workers are not perfect substitutes, and replacing workers might generate productivity losses especially in firms that rely on high-skilled labor. These firms might have lower productivity and wages because new workers are less skilled or they need time to accumulate firm specific human capital, or because of an increase in turnover costs in recruiting new workers.

Consequences of losses of workers might also depend on the intensity of the outflows. Results so far show that the number of firms in treated municipalities decreased, surviving firms have managed to keep employment constant while suffering big productivity losses. They nevertheless become more capital intensive. Firms in the 15-30 minutes bin who survive and suffer fewer losses instead keep their employment constant, pay their workers more, do not suffer productivity losses, and become more capital intensive. To better understand these results I implement a heterogeneity analysis based on the skill intensity of the sectors in which these firms operate.

6 Conceptual framework and mechanisms

From a theoretical perspective, there are several reasons why a negative shock might not have symmetric effects to a positive shock. For example, an inflow of workers should be absorbed, might have displacement effects and impact investments decisions. A loss of workers might generate instead search and training costs for the firm and a loss of knowledge spillovers among workers.

The empirical evidence on effects of a labor supply shock on Italian firms at the border shows

[68] I calculate a firm's TFP using a standard Cobb-Douglas production function: $Y = zK^{\alpha}L^{1-\alpha}$. I measure output Y with value added, capital K with total assets, and labor L with employment. Elasticities are estimated following Wooldridge (2009) and Levinsohn and Petrin (2003). This gives me my TFP measure z. All nominal values are deflated using sector specific GDP deflators to 2015 values.

that these firms keep employment constant while having lower wages, lower productivity, and higher capital. These results are not in line with the standard production function framework with constant returns to scale and homogeneous labor. In this setting, an outflow of workers, when nothing else changes, would result in higher wages at the firm, or in lower employment if wages are rigid. In this section I highlight the possible mechanisms behind each of these effects thinking about a simple production function with high and low-skilled labor as inputs while evaluating my results as adjustments of the different components of this production function following an outflow of workers.

Consider the general production function of a tradeable local good $Y_{m,t}$ in market m at time t. This good is produced with skilled and unskilled labor inputs $H_{m,t}$ and $L_{m,t}$, with labor specific productivity $\theta^H_{m,t}$ and $\theta^L_{m,t}$, together with physical capital $K_{m,t}$ and is a function of local productivity $A_{m,t}$. This production function can be written as follows

$$Y_{m,t} = F(A_{m,t}, K_{m,t}, \Lambda(\theta^H_{m,t} H_{m,t}, \theta^L_{m,t} L_{m,t})) \tag{3}$$

The effects of labor outflows can be modeled as a decrease in $H_{m,t}$ and $L_{m,t}$. Assuming that nothing else changes in the production function, the marginal product of the remaining workers would increase, as the marginal product of labor is now higher, implying higher wages for all workers. This is not what I find in my empirical results on firms close to the border (0-15 min). The observed effects instead require (i) lower wages at the firm, (ii) lower productivity, and (iii) higher capital per worker. One of the most plausible mechanisms is a change in the skill composition of the high-skill intensive firms.

The wage effect can be seen either as the consequence of a change in the mix of high and low-skilled labor inputs (through a composition and a replacement effect), or as a decrease in labor specific productivity of the new workers. First, high-skill intensive firms might suffer greater losses from high-skilled workers. This pure composition effect would imply that the workers who stay at the firm are the less productive ones, with lower wages. The replacement effect would imply that firms replace high-skilled labor with low-skilled one, because of scarcity of high skilled workers in the market. This would imply a lower wage both for incumbent and newly hired workers at high-skill intensive firms. Even if firms are able to replace the skills lost, it might take time for a worker to acquire firm-specific human capital. This would result in a decrease of labor specific productivity $\theta_{m,t}$ implying a lower wage for newly hired workers only at high-skill intensive firms. At the same time, if low-skill intensive firms rely on low skill labor only, the negative effects might be mitigated and more aligned with the standard model.

The productivity effect instead can be thought as the consequence of several channels following the changes in labor force composition. A change in the labor mix could result in a contraction of knowledge spillovers.[69] If $A_{m,t}(\cdot)$ is a function of the labor mix, or there is a loss in labor specific productivity $\theta_{m,t}$ firms might incur in productivity losses.

An effect of losses in productivity is that firms should avoid entering losing sectors where the labor factor is scarce. This would imply fewer firms entering especially high-skill intensive markets.

Finally, firms might invest in new technologies that are more productive in the most abundant labor factor. In this respect, all firms might become more capital intensive: high-skill intensive ones to increase productivity of lower skilled workers, and low-skill intensive ones because they only rely on low-skilled labor.

This framework shows that a loss in wages and productivity is consistent with a mechanism where losses of labor leave firms with a lower quality labor force, and translates into productivity detrimental effects leading to lower firm creation and accumulation of capital to complement low-skilled labor. The next section shows empirical evidence consistent with the above mechanisms performing an heterogeneity analysis where I divide firms into low and high-skill intensive ones.

6.1 Mechanisms

In this section I highlight how each sector experiences exits of workers and show results are consistent with the above mechanisms. First, I document that negative wage effects on incumbent and newly hired are indeed driven by high-skill intensive firms. Second, I show these firms suffer losses in productivity. Third, I analyze firm creation across low and high-skilled industries. Fourth, I present evidence on accumulation of physical capital. Finally, I discuss additional evidence on the labor force composition of these firms. To implement this heterogeneity analysis I group firms into four categories: high-tech (such as engineering, chemical, technological firms) and low-tech manufacturing, knowledge intensive services (such as financial and communication firms), and traditional not knowledge intensive services. Besides dividing firms into high and low-skill intensive sectors, I also distinguish between services and manufacturing to make sure there are no differences that might be possibly driven by demand effects in tradeable industries which belong to the manufacturing sector.

[69]See Kerr et al., 2015; Peri et al., 2015b.

Exits and employment Figure 7 shows the distribution of exits across the four sectors. All sectors suffer greater exits from their labor force. The only exception are knowledge-intensive (financial, real-estate, communication) service firms that do not display higher exits.[70] In the rest of the analysis I will therefore focus on firms in manufacturing and traditional services. Tables 9 and 10 show that exits are equally widespread in each sector across all the four quartiles of the wage distribution, meaning that on average firs do not lose more high or low paid workers. Finally figure 8 shows that all sectors are able to replace the worker who exit and keep employment constant.

Wage effects The first prediction of my conceptual framework is consistent with lower wages being driven by high-skill intensive firms. Table 6 and Table 7 decompose the effect on average wages in free access across the four sectors for firms in the 0-15 min and 15-30 min bin. Panel (a) reports estimates on all sectors. For treated firms in the 0-15 min bin the negative wage results are significant for high-skill intensive firms. Wages in high tech manufacturing (panel B) are 2.5% lower for incumbent workers (column 3) and almost 7% lower for newly hired ones (column 6), controlling for workers' fixed effects. Columns (4) and (7) report estimates on the average AKM[71] of these workers. The effects are either positive or insignificant. These result point toward a decrease in workers' wages due to a lack of firm specific skills, especially among newly hired workers. Panels (C) and (E) show that workers in low tech manufacturing and traditional services do not suffer any wage losses, incumbent workers in these sectors experience instead higher promotions. Table 7 shows the effects for firms in the 15-30 min bin, where losses of workers are much weaker. In this case workers in high tech manufacturing (or knowledge intensive sectors - panels B and D) experience weakly negative or zero wage losses. Workers in low-skill intensive firms, especially in manufacturing, show instead positive wages changes for incumbent and newly hired workers (around 1%), with a significant increase in the share of promotions. Finally, estimates on AKM show that workers in these firms are not lower-skilled. Results of low-skill intensive firms are instead consistent with the standard production function framework where incumbents have a higher marginal productivity and therefore receive higher wages.[72] Using survey evidence from INVIND data, available at the bank of Italy, table 27 in appendix E provides suggesting evidence on whether firms in these groups

[70] This can be due to the fact that labor mobility in these sectors is typically higher.

[71] Abowd et al. (1999).

[72] These results are also consistent with bargaining models where firms raise wages to prevent incumbents to leave the firm. This is consistent with the findings of Hafner (2019) where he finds French firms to pay higher wages to low-skilled workers.

report issues in finding adequate workers.[73]

Productivity effects The second prediction implies that following a huge turnover, and taking time for workers to acquire firm specific knowledge, firms might suffer from productivity losses (especially high-skilled and manufacturing firms). Figure 9 shows the estimates on productivity (value added) per worker and figure 10 shows estimates on TFP in the free access phase. Panel (a) reports the estimates for firms in the 0-15 min bin. Point estimates are negative for manufacturing and high-skill intensive sectors.[74] The effects are large in the range of 3-10% higher productivity losses. Panel (b) shows that for firms in the 15-30 min bin only high-tech manufacturing firms suffer productivity losses, even with weaker outflows. The effects on knowledge intensive services are however widely imprecise. Low-skill intensive firms do not show large productivity losses in traditional services. Table 29 in appendix E provides additional evidence on how these losses on workers might translate into productivity losses through fewer patents filed in treated firms. Though not significant, treated firms show a lower share of patents filed compared to control firms.

Firm creation The third prediction of my framework is that firms should entering sectors experiencing productivity losses, and for which skills are scarce in the labor market. Figure 11 shows the effects of firms creation in municipalities within 0-15 min from the border (panel (a)) and between 15-30 min from the border (panel (b)).[75] Regressions are at the municipality level and the dependent variable is the total number of new firms over the total number of firms in 1998 in a municipality. The figure shows a 5.7 percentage point lower share of manufacturing firms and a 7 p.p. higher share of traditional services firms. The effects in moderately treated firms (15-30 min) go in the same directions but are not statistically different than zero.

Capital accumulation The last prediction of my framework implies that firms might invest in new technologies that are more productive in the most abundant labor factor. Such a mechanism would imply a higher investment in physical capital to complement the skills left on the market. In this respect all firms might become more capital intensive: high-skill intensive ones to increase productivity of lower skilled workers, and low-skill intensive ones because they only rely on low-skilled labor. Figure 12 decomposes the effect on capital accumulation across the four sectors

[73] Firms in treatment groups report fewer training weeks for new workers in 2007, however they report a lower share of adequate workers for the job post, and that their location is an issue with finding new workers.

[74] Table 11 and Table 12 report the full effect in transition and free access phase for treated (0-15 min) firms, and moderately treated (15-30 min) firms.

[75] Full estimates for the transition and free access phase are reported in Table 13.

with treated firms in panel (a) and moderately treated ones in panel (b).[76] This figure shows all firms accumulate more capital. Point estimates are not significant. Overall positive coefficients are higher in low-skill intensive sectors, while negative in high-tech manufacturing within 15 minutes and knowledge intensive firms within the 15-30 min bin. This is in line with the idea that firms might be trying to complement lower skill labor with new technologies. Table 28 in appendix E, using data from the INVIND survey, provides additional suggesting evidence on which kind of capital treated firms invest. After 2004 treated firms increase by 20 percentage points their share of expenditures over intangible assets, while decreasing the share of expenditures over machines and real estate.[77]

Composition of the labor force Here I present additional supporting evidence on how low-skill intensive firms replace more easily the workers they lost. These firms employ more people from traditionally disadvantaged categories in the labor market: their labor force becomes younger, less experienced and features a higher share of women and foreigners. All these effects are absent in knowledge intensive firms. Tables 16 and 17 show the effect of labor market integration on other outcomes relative to the labor force composition at the firm for firms in the 0-15 minutes and 15-30 minutes bin respectively. Both tables decompose total effects according to the skill intensity of the sector of the firm. Column 2 and 3 show that low-skill intensive firms both in the 0-15 min and 15-30 min bin have a younger and less experienced labor force compared to the same firms in the control group. The estimates are significant for firms in the 0-15 min bin with a 1% younger and 5% less experienced labor force in service firms. The share of women in service firms within the 0-15 minutes bin is also 2.6 percentage points higher than in firms in the control group. The effect takes place mostly in the first years after the policy reform. The same increase is as big as 2 percentage points in moderately treated firms (15-30 min) and is driven by low-skill intensive firms. For firms in the 15-30 minutes bin, I also observe a 2.9 percentage points increase in the share of foreign workers in traditional service industries. These results imply that, following an outflow of workers, low-skill intensive firms, who have a large pool of substitutable workers to hire from, are able to replace their workers, pay them higher wages, and they resort to younger and less experienced workers, increasing the participation of women and foreigners in the labor market. In the next section, I discuss my results in the light of their contribution to the economics' literature.

[76] Full estimates for the transition and free access phase are reported in column (6) of Table 11 and Table 12.

[77] Given the limited dimension of the survey and the size requirement, there are only around 15 firms in the treatment group. Evidence produced with this data should be then taken as purely suggestive.

7 Discussion of the literature

My paper contributes to the literature on brain drain bridging the gap between losses of human capital and consequences on productivity by showing how these effects act through the firms who lose workers. The brain drain literature highlights how an outflow of workers can have both negative or positive consequences in terms of productivity and human capital accumulation. With the exception of Giesing and Laurentsyeva (2018), macro and micro evidence so far, document the effects of emigration on human capital accumulation overlooking however the role of firms. Theoretical work of Wong and Yip (1999) and Haque and Kim (1995) shows that negative consequences on productivity and growth happen when the stock of human capital is exogenous, or when the additional creation of human capital ends up abroad.[78] Explicitly linking for the first time losses of workers within firms to their performance, my results document that negative effects act in the labor market through productivity losses and lower entrance of high-skilled firms. Surviving high-skill intensive firms suffer productivity losses which can be reconnected to a labor force lacking and needing time to acquire firm-specific knowledge. The loss of high skilled workers, and the negative effects on firm creation are also studied by Anelli et al. (2020). In line with my findings, they document lower firm creation in Italy in the regions most affected by emigration of young Italian workers. I show that firm creation is lower in high-skill intensive sectors and manufacturing, and low-skill intensive - traditional services in particular - are less exposed to negative consequences in the country of origin. If anything, the higher outflows of unskilled workers generates new labor market opportunities for low-skilled workers who do not migrate. A less pessimistic literature (Mountford, 1997; Stark et al., 1997; Beine et al., 2001; Vidal, 1998; Stark et al., 1998) argues that positive effects can happen under two conditions: that differential skills' prices between source and destination country is low enough to generate incentive effects in investment, and that the probability of high-skilled emigration is low.

My evidence on firms has important consequences in terms of sharpening policy implications in an effective way. One major policy to limit negative effects on high-skill intensive firms would be to reduce the gap in high skill prices between the country of origin and destination paying high-skilled workers more. One way to do that would be to increase R&D investment with the idea of making

[78] Kremer (1993) shows this effect can also act through occupational shortages. Cross country analysis of Beine et al., 2001, 2008 documents that human capital formation is stronger in source countries with low initial levels of GDP per capita. Empirical micro evidence is limited to Batista et al. (2012) showing that in Cape Verde, the possibility of emigrating led students to invest in additional classes.Chand and Clemens (2008) document similar results for Fijians of Indian ancestry.

processes more efficient and reducing labor costs. It is important however, to target these measures to the most technological and productive firms.

Negative effects of workers' outflows can be strengthened or loosened through network effects[79], educational subsidies, occupational choices, and fertility. The last two are particularly relevant in my context. One policy option would be to provide education incentives targeted to occupational choices crucial in highly productive firms.[80] The fertility channel might be particularly interesting for developed countries.[81] Many high income countries are today facing sinking fertility rates. This could result into a vicious cycle where high-skilled emigration and lower fertility rates reinforce each other increasing over time labor market tightness of high skilled workers. A final policy implication might be to provide broad incentives to workers to return[82] such as lowering the amount of social security contributions paid by the employer when hiring high-skilled returning workers.[83]

My paper relates to a recent strand of the literature on immigration.[84] This literature has focused on technology adoption and human capital accumulation in the country of origin from historical migration.[85] To the best of my knowledge, this is the first paper observing losses of workers within a firm, and studying the effects of these outflows on the firms in the country of origin of the migrants. Hafner (2019) studies the impact of labor market integration between Switzerland and France on the french labor market. While he finds no effects on high-skilled french workers, he also finds that low-skilled workers have higher wages.

Very few papers have focused on effects on firms, and all of them have done so in the light of a positive shock to labor supply following migration inflows.[86] A very closed work is the paper of

[79] See Benhabib and Spiegel, 2005; Vandenbussche et al., 2006; Agrawal et al., 2011

[80] For e.g. engineers, managers, technicians, computer scientists.

[81] Beine et al. (2008) document that what matters most is not how many people invest in higher education, but the number of high-skilled individuals remaining in the country after emigration takes place. Mountford and Rapoport, 1997, 2011 endogenize fertility and show high skilled emigration might reduce fertility rates.

[82] This is typically done in the form of tax exemptions for returning immigrants.

[83] Another policy is to attract high-skilled labor from other lower-income countries. This is sub-optimal for the country who lost skills because skills from abroad are typically less productive than native ones (see Coulombe and Tremblay (2009)) and impose losses to the source country of these immigrants. This paper shows suggestive evidence this happens in the Italian context, with larger share of immigrants working in firms who replaced workers who moved to Switzerland. A large literature focuses on remittances. Grubel and Scott (1966) started this literature, for a review see Docquier and Rapoport (2012). Remittances might be helpful only to the extent that they are invested in higher education.

[84] The majority of the migration literature focuses on the impact of immigration on the wage structure of natives (see Grossman, 1982; Altonji and Card, 1991; Goldin, 1994; Borjas et al., 1997, 1996; Card, 2001; Angrist and Kugler, 2003; Borjas, 1999, 2003; Manacorda et al., 2012; Ottaviano and Peri, 2012; Monras, 2019).

[85] Andersson et al. (2020) studies historical mass migration in the 19th century from Sweden to the Unites States finding a faster technology adoption and higher wages in the agricultural sector. Clemens et al. (2018) look at the exclusion of bracero Mexican workers from US farms finding no effect on the participation of US workers and a higher investment in technology in the agricultural sector. Fernandez-Sanchez (2020) focuses on effects of the Galician diaspora on human capital accumulation. He finds higher investments in human capital in the long run.

[86] Kerr et al. (2015) provide an overview of the effects of immigration on productivity, innovation, production tech-

Beerli et al. (2018). They study the impact of the same labor market integration on Swiss natives' wages and Swiss firms. They find the outflow of high-skilled EU immigrants in Switzerland had a positive effect on both low and high-skill natives' wages, and an increase in entry of innovative firms. My results complement their analysis in that I find higher firm destruction in the Italian labor market both from an increase in exits of firms, and from a lower firm creation in the bordering regions. Also, I show that the loss of high skilled workers, benefiting Swiss firms, harmed Italian firms relying on high-skilled labor.

My results speak more broadly to the literature on human capital specificity of wage effects (Becker, 1962; Oi, 1962; Parsons, 1972; Hashimoto, 1981; Jäger, 2016) in which firms renegotiate wages of stayers when they have a credible outside option.[87] The fact that wage effects are positive or zero in low-skill intensive firms and negative in high-skill intensive ones shows that wages and productivity depend on labor market tightness, substitutability of workers, and bargaining power with respect to the Swiss outside option. The case of high-skill intensive firms specifically points to the tightness channel.[88] The results on capital speak in favor of endogenous choice of technique or multisector models rather than models with separable capital or capital-skills complementarities [89].

Finally, this paper relates to the works of Parenti and Tealdi (2019) and Bello (2020) who analyze the effects of the implementation of the Schengen area and of fluctuations in the exchange rate on the increase in commuting between Italy and Switzerland.

8 Conclusions

In this paper, I document how adverse effects of workers' losses operate through firms that these workers leave. I study the adjustment of Italian firms to negative labor supply shocks in the context of migration outflows from Italy to Switzerland, linking losses of labor within each Italian firm, to their performance. I leverage on the implementation of a policy in which Switzerland granted free

nology in the receiving country. Some firm-level studies examining the link between immigration and firm performance reach different conclusions (see Dustmann et al., 2016; Hunt and Gauthier-Loiselle, 2010; Peri, 2012; Peri and Sparber, 2009, 2011; Peri et al., 2015a,b; Moser et al., 2014; Doran et al., 2014; Dustmann and Glitz, 2015; Ghosh et al., 2014; Mitaritonna et al., 2017; Dustmann et al., 2017).

[87] My results are consistent with models of intra-firm bargaining with industry specific human capital such as De Fontenay and Gans (2003). My results conflict with the model of Stole and Zwiebel (1996a) which predicts over-employment when human capital is firm-specific.

[88] These firms face high search frictions in finding substitutable skills resulting into lower wages. In particular, knowledge intensive firms do not suffer higher exits of workers yet, the lower wages can be explained if these firms find it hard to hire high-skilled workers. As Moretti (2011) shows firms fill in vacancies more easily when they face a tight labor market.

[89] See Lewis (2013)

labor market mobility to EU citizens. I implement a diff-in-diff specification leveraging on the timing of the reform and on different treatment intensity of Italian firms based on the distance from the Italian firm to the Swiss border. I find that regions closer to the Swiss border lose 2 percentage points of firms. Surviving firms replace the workers they lost and become more capital intensive however, they pay lower wages and become less productive. I explain my results in the lights of a simple production function framework allowing for high and low-skilled labor. I provide suggestive evidence that high-skill intensive firms are the main driver of the negative results on wages and productivity. I also show that low skill intensive firms instead do not suffer from losing workers and provide new job opportunities for the workers who do not migrate. My research calls for further evidence on different topics. One mechanism that needs further investigation is firms' investment decisions on physical or human capital when skills are scarce. A second mechanisms that needs investigation is how losses of workers might generate a broader reshuffle of remaining workers across firms and how the exit of a coworker affects employment decisions of his peers. More evidence would be also crucial to understand how some local labor markets attract high-skilled workers generating tightness and wage depression in the neighboring markets. Finally, additional evidence would help understanding the role of turnover's costs and how they relate to market tightness of specific skills.

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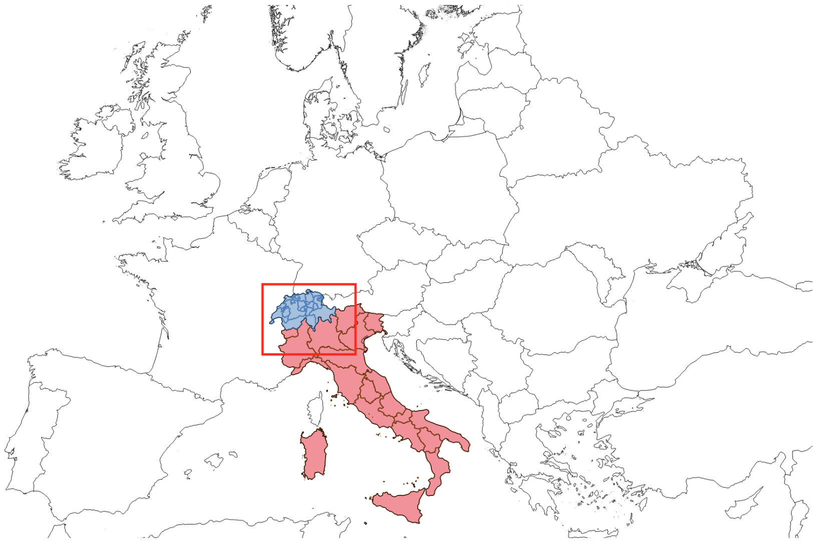
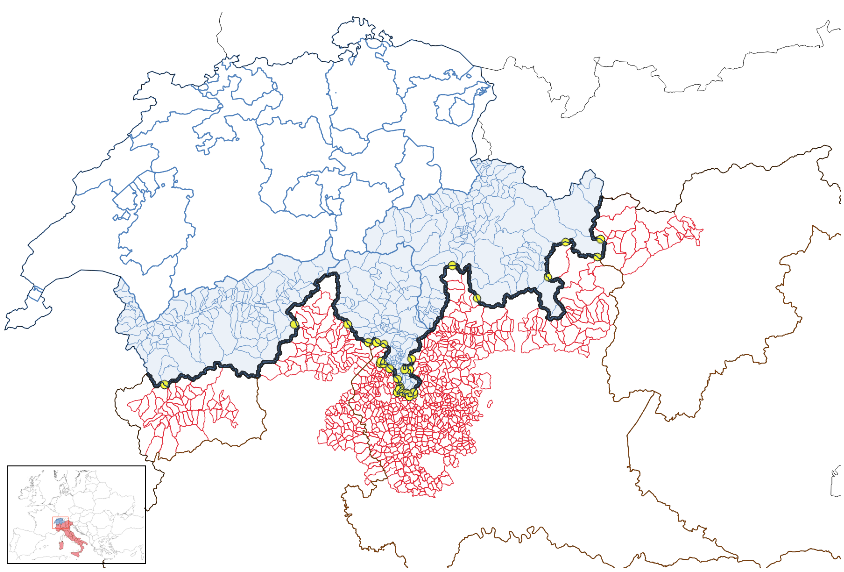
A Figures and tables

Figure 1: Map of the Swiss-Italian border

(a)



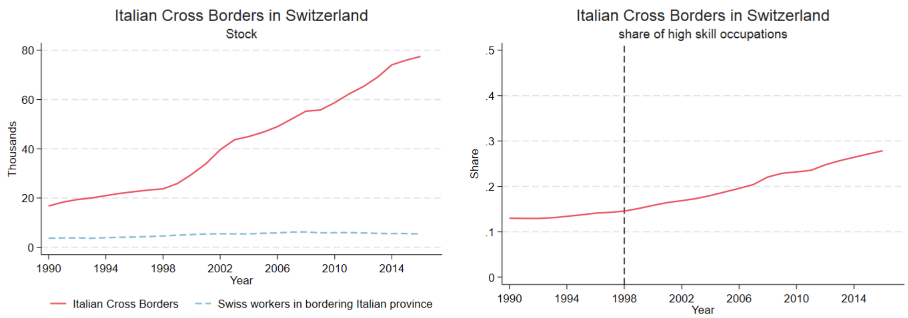
(b)



Notes: Panel (a) shows a map of Italy (red) and Switzerland (blue). Panel (b) zooms into the border of the two regions and shows the bordering Swiss cantons together with the closest Italian municipalities for which I have the commuting distance to the closest border crossing (orange dots).

Figure 2: Italian Immigrants to Switzerland

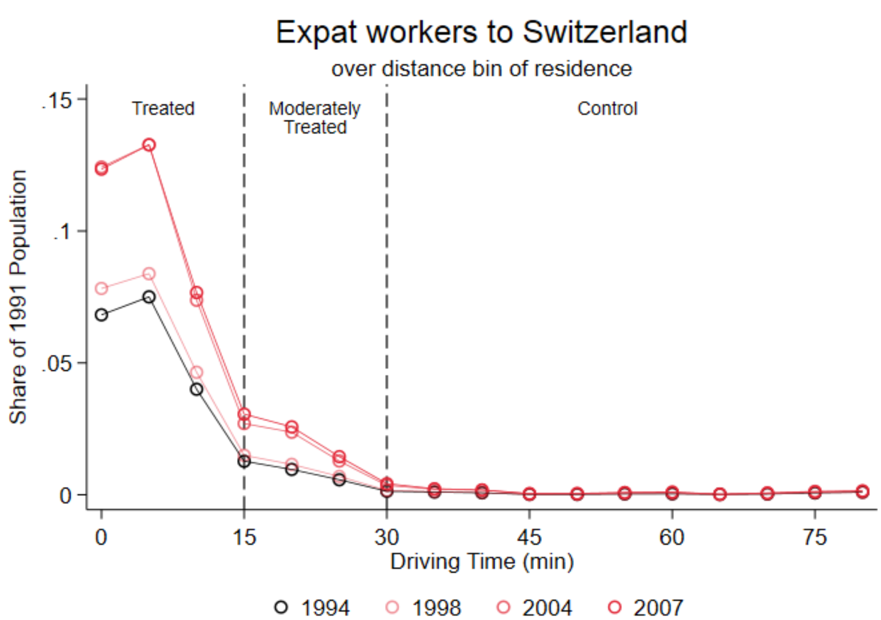
(a) Stock (b) Share High Skilled



Notes: This figure plots descriptive statistics about Italian and Swiss workers. Panel (a) plots the stock of Italian cross border workers (continuous red line) from 1990 to 2015 from Swiss social security data together with the stock of Swiss workers in the Italian regions in my sample (dashed blue line). Panel (B) plots the share of Italian cross borders in a high skilled occupation. High skilled occupations are ISCO codes 1,2, and 3.

Figure 3: Share of expat workers on Italian population in 1991 by distance bin of residence

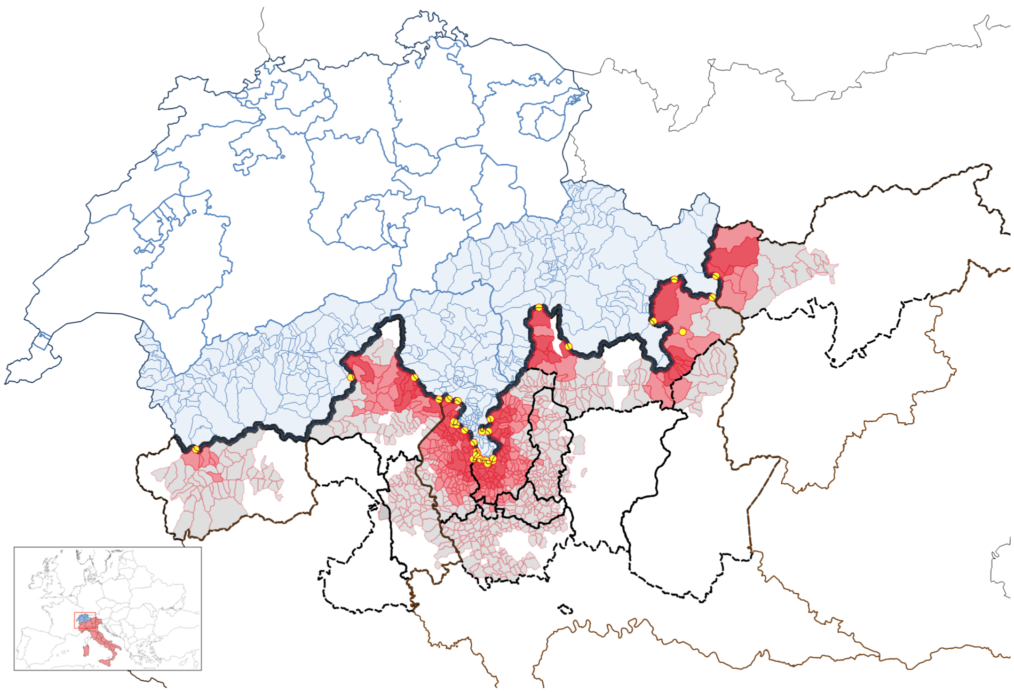
(a) Stock



This figure plots expat workers per municipality as share of 1991 Italian population. Municipalities are ranked on the x axis according to the driving distance to the Swiss border and grouped within five minutes bins. Each line is for a different sample year from 1994 to 2007. Swiss data, foreign residents data, and distance data.

Figure 4: Map of Treatment and Control groups

(a)



Notes: This figure shows treatment and control groups of municipalities at the Italian border. Border crossings are yellow dots. Province NUTS III border are delimited by a dashed black line. Treated firms are in a commuting bin of 0-15 minutes to the closest border crossing (dark red). Moderately Treated firms are in a commuting bin of 15-30 minutes to the closest border crossing (light red). Control firms are in a commuting bin of more than 30 minutes to the closest border crossing (light gray).

Table 2: Summary DID Table before 1998

	(1) Pre 1998 Control Group	(2) Pre 1998 Moderately Treated	(3) Pre 1998 Treatment Group	(4) Pre 1998 Difference (2)-(1)	(5) Pre 1998 Difference (3)-(1)
Panel A: Labor Outcomes					
FTE Exits on 98 Size	0.030	0.034	0.042	0.0039	0.012
	[0.096]	[0.089]	[0.099]	(0.00051)**	(0.00087)**
Yearly Share of Exits	0.012	0.013	0.017	0.0015	0.0052
	[0.052]	[0.051]	[0.057]	(0.00028)**	(0.00047)**
Share of Hirings	0.24	0.24	0.25	-0.00015	0.014
	[0.54]	[0.34]	[0.31]	(0.0027)	(0.0047)**
Share of Separations	0.20	0.20	0.22	0.0047	0.017
	[0.86]	[0.35]	[0.30]	(0.0042)	(0.0075)*
Share of JTJ within 1 month	0.070	0.068	0.062	-0.0022	-0.0073
	[0.62]	[0.22]	[0.14]	(0.0030)	(0.0054)
Employment Growth	0.11	0.11	0.11	-0.0043	-0.0028
	[0.91]	[0.43]	[0.40]	(0.0045)	(0.0080)
Turnover	1.13	1.15	1.21	0.024	0.078
	[3.38]	[1.41]	[1.38]	(0.017)	(0.029)**
Share of Promotions	0.028	0.031	0.033	0.0028	0.0046
	[0.084]	[0.080]	[0.082]	(0.00045)**	(0.00075)**
FTE total employees in year (share)	14.3	13.3	12.4	-0.92	-1.81
	[25.6]	[23.4]	[21.5]	(0.13)**	(0.23)**
Mean weeks PC	40.4	39.8	38.6	-0.64	-1.81
	[10.4]	[10.7]	[11.4]	(0.056)**	(0.094)**
Mean Weekly Wage	485.0	452.5	452.1	-32.5	-32.9
	[206.7]	[163.8]	[166.3]	(1.07)**	(1.83)**
Mean Weekly Imponibile	482.1	449.7	449.2	-32.4	-32.9
	[200.7]	[158.0]	[161.9]	(1.04)**	(1.78)**
Panel B: Firm Characteristics					
Firm closure in the year	0.0085	0.0088	0.0093	0.00031	0.00086
	[0.092]	[0.093]	[0.096]	(0.00049)	(0.00082)
Firm Active today	0.38	0.38	0.36	0.0027	-0.017
	[0.48]	[0.49]	[0.48]	(0.0026)	(0.0043)**
Value Added	1391.8	1319.7	1313.1	-72.1	-78.7
	[2794.2]	[2491.2]	[2517.7]	(35.0)*	(63.1)
Total Assets	1053.5	1020.5	1105.8	-32.9	52.4
	[2823.7]	[2519.8]	[2757.2]	(34.4)	(62.1)
High-Tech Manufacturing	0.26	0.18	0.14	-0.080	-0.13
	[0.44]	[0.39]	[0.34]	(0.0023)**	(0.0039)**
Low-Tech Manufacturing	0.35	0.43	0.37	0.079	0.022
	[0.48]	[0.50]	[0.48]	(0.0026)**	(0.0043)**
Not Know. int. Service	0.28	0.29	0.36	0.0044	0.082
	[0.45]	[0.45]	[0.48]	(0.0024)	(0.0041)**
Know. int. Service	0.11	0.10	0.13	-0.0035	0.022
	[0.31]	[0.30]	[0.33]	(0.0016)*	(0.0028)**
MRA affected	0.54	0.57	0.49	0.022	-0.055
	[0.50]	[0.50]	[0.50]	(0.0027)**	(0.0045)**
Has CERVED var.	0.23	0.18	0.16	-0.053	-0.069
	[0.42]	[0.38]	[0.37]	(0.0022)**	(0.0038)**
Panel C: Firm Composition					
Women	0.35	0.39	0.38	0.037	0.034
	[0.64]	[0.40]	[0.38]	(0.0032)**	(0.0056)**
Foreigners	0.036	0.037	0.040	0.0018	0.0046
	[0.11]	[0.10]	[0.12]	(0.00058)**	(0.00098)**
Share Blue Collars	0.60	0.62	0.59	0.020	-0.014
	[0.34]	[0.33]	[0.35]	(0.0018)**	(0.0031)**
Share Part-Time	0.075	0.076	0.091	0.0014	0.016
	[0.16]	[0.16]	[0.18]	(0.00088)	(0.0015)**
Share Fixed term contract	0.014	0.014	0.014	-0.00013	-0.00031
	[0.067]	[0.069]	[0.068]	(0.00036)	(0.00060)
Panel D: Firm Distance					
Driving km from firm to border	48.5	21.3	8.70	-27.2	-39.8
	[12.7]	[6.96]	[2.98]	(0.063)**	(0.11)**
Driving min from firm to border	47.0	24.7	12.6	-22.3	-34.4
	[9.71]	[4.24]	[3.59]	(0.048)**	(0.085)**
Number of obs	189115	42735	13300	231850	202415
Number of firms	42710	9487	2964	52197	45674

Notes: The table shows average firm characteristics in the three treatment groups. Column (1) shows characteristics of firms in the control group ($d_j > 30min$). Column (2) shows characteristics of firms in the 15-30 minutes min from the border (moderately treated). Column (3) shows characteristics of firms in the 15 minutes min from the border (treated). The data are from INPS. Entries represent averages per region of all firm-year observations in the pre-treatment years from 1994 to 1998. Columns (2) and (3) report mean differences between moderately treated and treated firms with control firms respectively. Standard errors report statistical significance (*<.05, ** P<.01).

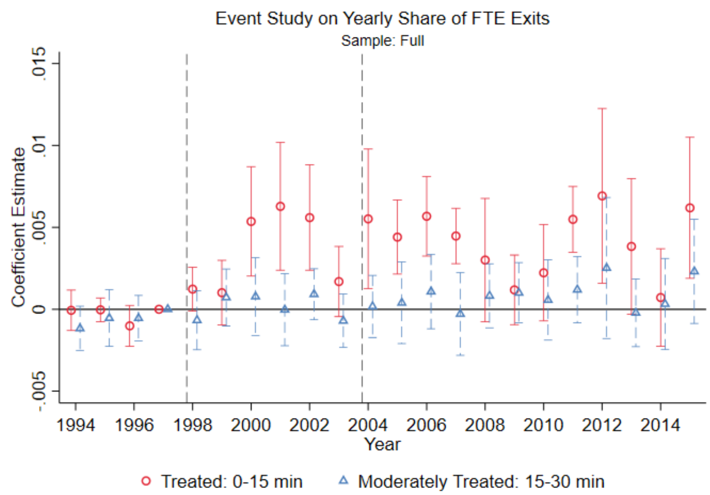
Employment dynamics and wages In panel A the share of exits ranges between 1% and 2% with treated firms already experiencing a significantly higher share of exits, which has a magnitude of 0.2-0.9 percentage points. The same is true for the share of separations which is 4 percentage points higher in the treatment group. The hiring rate is instead 1.5 percentage points higher in the treatment group and 0.8 percentage points lower in the moderately treated firms. There is no significant difference instead in job to job transitions and promotions. The average firm in the control group has 14.6 FTE employees. Firms in the moderately treated group have 1 FTE employee less, while treated firms are almost 2 FTE employees smaller than firms in the control group. The average number of weeks worked is around 39 in the control group. Compared to them, treated firms have on average 2 weeks of work less while moderately treated firms work 0.6 weeks less. Also, treated firms pay on average 31 to 36 euros less per week compared to an average 497 euros per week in the control group.

Characteristics of the firm Panel B shows there is no difference between the three groups in the number of firms that closed in 1998, or in the number of firms that still exists today. The treatment group has a 33% of firms in manufacturing compared to 47% in the control group. The same share is 5.9 percentage points lower in the moderately treated group. Both treatment groups have fewer tradable firms and fewer incoporated firms. Finally, Treated firms have a lower number of firms affected by reduction in trade costs than in the control group, while this number is higher in the moderately treated group.

Characteristics of workers The share of women is 4 percentage points higher in both treatment groups where 40% of the labor force is female. 60% of workers in the control group have a blue collar qualification. This number is 2 percentage points higher and 1.9 percentage points lower in the moderately and treated firms. Treated firm have a significant 1.7 percentage points higher share of part time workers. Finally, there is no significant difference across the three groups in the share of foreigners and fixed contract is the same in the three groups.

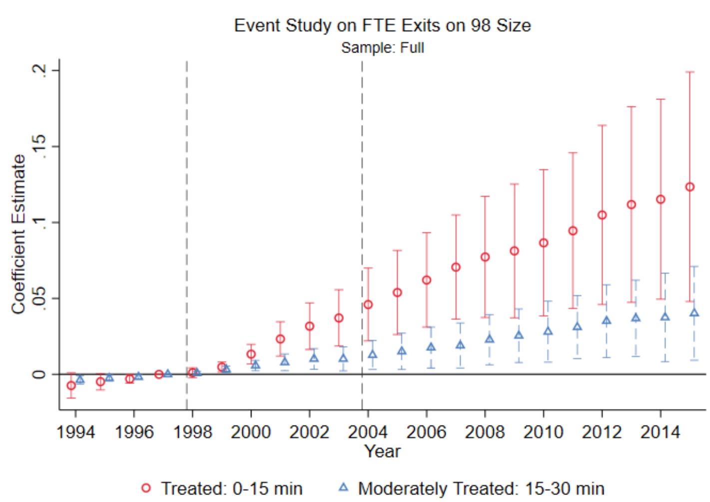
Distance According to the rules of treatment assignment the average firm in the control group is 47 minutes away from the border. The average treated firm is 24.7 minutes away from the border, the average treated firm is 12.6 minutes away from the border.

Figure 5: Exits of Italian Workers: Flows



Notes: This figure plots coefficient and the 95% confidence interval for firms in the 0-15min distance bin (red circles) and in the 15-30 min distance bin (blue triangles) of a regression based on equation (2). The dependent variable is yearly full-time equivalent (FTE) exits over total employment in 1998. Regressions are weighted using the total workforce in 1998 in a cell and include NUTS III trends and a Bartik control for shifts in employment. Standard errors are clustered at the local labor market level. INPS data.

Figure 6: Exits of Italian Workers: Stock



Notes: This figure plots coefficient and 95% confidence interval for firms in the 0-15min distance bin (red circles) and in the 15-30 min distance bin (blue triangles) of a regression based on equation (2). The dependent variable is cumulated full-time equivalent (FTE) exits over total employment in 1998. Regressions are weighted using the total workforce in 1998 in a cell and include NUTS III trends and a Bartik control for shifts in employment. Standard errors are clustered at the local labor market level. INPS data.

Table 3: Exits by quartile of 1998 wage distribution

	(1) Exits	(2) Exits Bottom Quart	(3) Exits Lower Mid Quart	(4) Exits Upper Mid Quart	(5) Exits Top Quart
			Panel A: Treated		
Transition×($d < 15$)	0.024	0.0071	0.0063	0.0069	0.0053
	(0.0062)**	(0.0029)*	(0.0021)**	(0.0013)**	(0.0014)**
Free×($d < 15$)	0.083	0.026	0.021	0.023	0.021
	(0.023)**	(0.012)*	(0.0058)**	(0.0049)**	(0.0049)**
Relative Effect	1.78	1.20	1.76	2.51	2.26
			Panel B: Moderately Treated		
Transition×($15 < d < 30$)	0.0086	0.0048	0.0016	0.0017	0.0014
	(0.0028)**	(0.0013)**	(0.00067)*	(0.00065)*	(0.0012)
Free×($15 < d < 30$)	0.026	0.013	0.0067	0.0072	0.0056
	(0.0095)*	(0.0043)**	(0.0023)**	(0.0022)**	(0.0040)
Relative Effect	0.56	0.59	0.55	0.77	0.60
Mean of Dep. Var.	**0.046**	**0.021**	**0.012**	**0.0093**	**0.0094**
Firm FE	X	X	X	X	X
Time FE	X	X	X	X	X
Nuts III trend	X	X	X	X	X
R2	0.68	0.62	0.67	0.67	0.63
F-stat	6.44	6.92	5.82	14.5	8.12
Observations	842421	842421	842421	842421	842421

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of establishment-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is cumulated full-time equivalent (FTE) exits over total employment in 1998. The dependent variable in column 2-5 is cumulated full-time equivalent (FTE) exits over total employment in 1998 of workers in each quartile of the residualized (with age, age squared, and gender) log wage distribution. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

Table 4: Entry and Exit of Firms

	(1) Net Entry	(2) Exit	(3) Entry
	Panel A: Treated		
Transition×($d < 15$)	-0.012	0.010	-0.0020
	(0.0059)*	(0.016)	(0.015)
Free×($d < 15$)	-0.026	0.030	0.0042
	(0.016)	(0.033)	(0.035)
Relative Effect	-0.26	0.15	0.014
	Panel B: Moderately Treated		
Transition×($15 < d < 30$)	-0.011	0.0083	-0.0024
	(0.0041)*	(0.016)	(0.013)
Free×($15 < d < 30$)	-0.021	-0.0026	-0.024
	(0.017)	(0.034)	(0.024)
Relative Effect	-0.21	-0.013	-0.079
Mean of Dep. Var.	**0.10**	**0.20**	**0.30**
Firm FE	X	X	X
Time FE	X	X	X
Nuts III trend	X	X	X
R2	0.77	0.96	0.94
F-stat	2.93	13.8	5.48
Observations	13740	13740	13740

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of municipality-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is cumulated net entry of firms over total number of firms in a municipality in 1998. Cumulated net entry is defined as number of new firms minus number of firms who exit cumulated over the years. The dependent variable in column 2 is cumulated exit of firms and dependent variable in column 3 is cumulated entry of firms both as a share of the total number of firms in a municipality in 1998. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

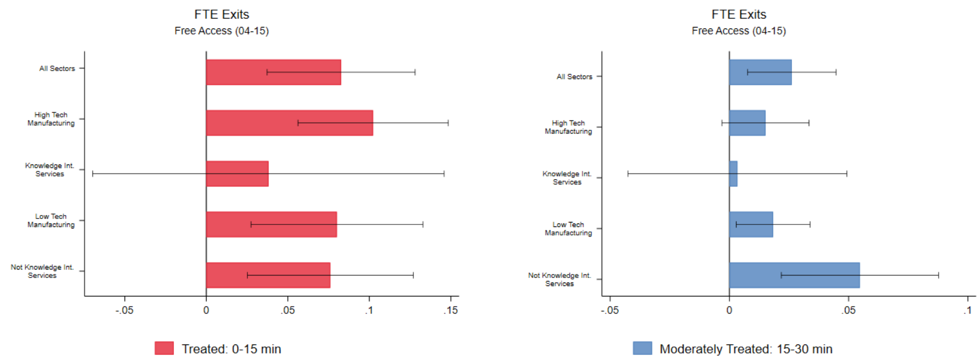
Table 5: Margins of adjustment

	(1) Log Firm Size	(2) Average Log Wage	(3) Log Value added per capita	(4) Log Value Added	(5) TFP	(6) Log Assets per capita
Panel A: Strongly Treated						
Transition×($d < 15$)	-0.011	0.0023	-0.065	-0.069	-0.072	0.055
	(0.016)	(0.0040)	(0.041)	(0.034)	(0.031)*	(0.050)
Free×($d < 15$)	-0.015	-0.014	-0.075	-0.076	-0.095	0.068
	(0.034)	(0.0054)*	(0.024)**	(0.033)*	(0.021)**	(0.021)**
Panel B: Moderately Treated						
Transition×($15 < d < 30$)	-0.016	0.0047	-0.0095	-0.035	-0.0087	0.0066
	(0.013)	(0.0023)*	(0.017)	(0.022)	(0.013)	(0.024)
Free×($15 < d < 30$)	-0.0064	0.0073	-0.0077	0.0041	-0.0033	0.069
	(0.020)	(0.0055)	(0.014)	(0.019)	(0.0096)	(0.022)**
Firm FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Nuts III trend	X	X	X	X	X	X
R2	0.87	0.43	0.61	0.86	0.69	0.75
F-stat	3.39	36.5	3.97	2.31	10.2	7.47
Observations	843287	19918528	270497	270497	267493	279970

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of establishment-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is log FTE employment. The dependent variable in column 2 is average log weekly wages, treatment is defined at the firm level but observations are workers within a firm. The dependent variable in column 3 is log value added per employee. The dependent variable in column 4 is log total value added at the firm. The dependent variable in column 5 is TFP. Total assets are tangible and intangible assets. The dependent variable in column 6 is log total assets per employee. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data and *Cerved* data. Columns 3-6 rely on firms for which balance sheets data are available. Results of column 1-2 on the restricted sample of *Cerved* firms are reported in table 24. Event studies on main outcomes are reported in figure 23. To limit concerns on the use of log employment, table 23 in appendix E reports the number of hiring, separations, and exits as share of employment in 1998.

Figure 7: Heterogeneity of exits

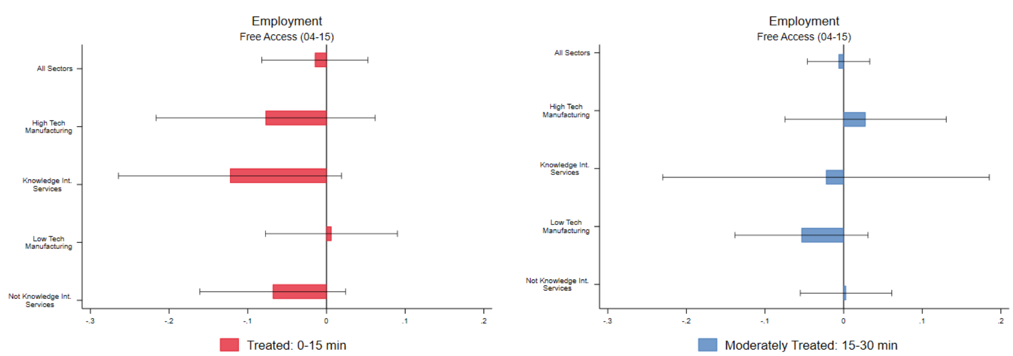
(a) Treated (0-15 min) (b) Mod. Treated (15-30 min)



Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red bars) and 15-30 min distance bin (blue bars) of a regression based on equation (1). The coefficients report estimates for the free access phase. Panel (a) shows the effect on 0-15min firms and panel (b) 0-30min firms. High-tech manufacturing is NACE Rev 2 industries 24, 29, 30, 31, 32, 33, 34 and 35 excluding 35.1. Low-tech manufacturers are the remainder manufacturing categories. Knowledge-intensive services are NACE Rev 2 industries 61, 62, 64, 65-67, 70-74, 80, 85, 92. Not knowledge-intensive services are the remainder service sector categories. Full estimates for the transition and free access phase are reported in Table 9 and Table 10. INPS data.

Figure 8: Heterogeneity of employment

(a) Treated (0-15 min) (b) Mod. Treated (15-30 min)



Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red bars) and 15-30 min distance bin (blue bars) of a regression based on equation (1). The coefficients report estimates for the free access phase. Panel (a) shows the effect on 0-15min firms and panel (b) 0-30min firms. High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. Full estimates for the transition and free access phase are reported in Table 11 and Table 12. INPS data.

Table 6: Heterogeneity of Wages

Strongly Treated - Free access

	All workers	Incumbent			Entrant			
	Log avg Wage	Log avg Wage	Log avg Wage	Avg AKM	Log avg Wage	Log avg Wage	Avg AKM	Share Promotions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. All Sectors								
Free$\times(d < 15)$	-0.0078	-0.013	-0.010	0.060	-0.028	-0.033	0.017	0.062
	(0.011)	(0.0063)*	(0.0098)	(0.022)***	(0.0100)***	(0.0099)***	(0.018)	(0.020)***
Observations	19216134	10807165	10711562	34846399	4166667	2409646	34846399	1111270
B. High-tech Manufacturing								
Free$\times(d < 15)$	-0.018	-0.022	-0.025	0.079	-0.082	-0.068	0.029	0.023
	(0.014)	(0.0097)**	(0.015)*	(0.035)**	(0.044)*	(0.017)***	(0.028)	(0.021)
Observations	4416320	2870239	2845455	7509789	638602	271047	7509789	232639
C. Low-tech Manufacturing								
Free$\times(d < 15)$	-0.0052	-0.013	-0.0070	-0.0065	0.015	0.0047	-0.00024	0.045
	(0.012)	(0.0090)	(0.011)	(0.0043)	(0.011)	(0.026)	(0.0024)	(0.0077)***
Observations	5056617	3001692	2973030	8236594	793882	364629	8236594	337536
D. Knowledge Intensive Service								
Free$\times(d < 15)$	-0.022	-0.024	-0.027	-0.0100	-0.017	-0.093	0.0095	0.025
	(0.014)	(0.013)*	(0.013)**	(0.022)	(0.021)	(0.031)***	(0.0033)***	(0.065)
Observations	4486243	2168455	2096335	9396012	1584939	638057	9396012	182351
E. Knowledge not Intensive Service								
Free$\times(d < 15)$	0.0061	0.0043	0.0035	0.0096	0.0013	-0.011	-0.016	0.045
	(0.0098)	(0.0052)	(0.0091)	(0.0057)*	(0.025)	(0.028)	(0.0060)***	(0.012)***
Observations	5023118	2757521	2721271	9408441	1146664	550263	9408441	356434
Firm and Time FE	X	X	X	X	X	X	X	X
Nuts III Trends	X	X	X	X	X	X	X	X
Worker FE	X	.	X	.	.	X	.	.

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) for treated firms in the 15 minutes bin $I(d_j \leq 15)$ weighted using the average establishment size (in FTE) as weight. While treatment is at the establishment level, the unit of observation is the single worker within an establishment. All regressions account for establishment fixed effects, period fixed effects, workers fixed effect, and linear trends per NUTS-III region. The dependent variable in column 1 is average log weekly wages for the full labor force. The coefficient in the first line of column 1 differs from the coefficient in column 2 of table 5 because workers fixed effects are included. The dependent variable in column 2 and 3 is average log weekly wages of incumbent workers. The dependent variable in column 3 is average AKM of incumbent workers. The dependent variable in column 4 and 5 is average log weekly wages of newly hired workers. The dependent variable in column 6 is average AKM of newly hired workers. Free is a dummy from year 2004 onward. The regressions are Estimates from full sample are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

Table 7: Heterogeneity of Wages

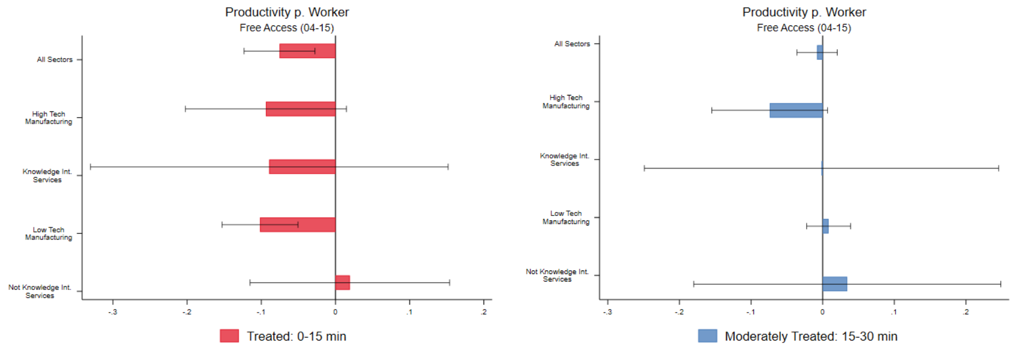
Moderately Treated - Free access

	All workers	Incumbent			Entrant			
	Log avg Wage	Log avg Wage	Log avg Wage	Avg AKM	Log avg Wage	Log avg Wage	Avg AKM	Share Promotions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. All Sectors								
Free×$(15 < d < 30)$	0.0079	0.0079	0.0057	0.048	0.0061	0.0010	0.0061	0.039
	(0.0033)**	(0.0033)**	(0.0029)*	(0.021)**	(0.014)	(0.012)	(0.014)	(0.019)**
Observations	19216134	10807165	10711562	34846399	4166667	2409646	34846399	1111270
B. High-tech Manufacturing								
Free×$(15 < d < 30)$	0.00021	0.0070	-0.0030	0.056	0.016	0.0055	0.0016	-0.0038
	(0.0043)	(0.0073)	(0.0041)	(0.041)	(0.0089)*	(0.025)	(0.027)	(0.017)
Observations	4416320	2870239	2845455	7509789	638602	271047	7509789	232639
C. Low-tech Manufacturing								
Free×$(15 < d < 30)$	0.0092	0.012	0.010	0.0073	0.013	0.0068	-0.000049	0.023
	(0.0038)**	(0.0044)**	(0.0036)***	(0.0053)	(0.0083)	(0.015)	(0.0055)	(0.014)*
Observations	5056617	3001692	2973030	8236594	793882	364629	8236594	337536
D. Knowledge Intensive Service								
Free×$(15 < d < 30)$	-0.019	-0.025	-0.020	0.012	0.0022	-0.034	0.016	0.054
	(0.010)*	(0.011)**	(0.010)*	(0.011)	(0.021)	(0.020)*	(0.0049)***	(0.035)
Observations	4486243	2168455	2096335	9396012	1584939	638057	9396012	182351
E. Knowledge not Intensive Service								
Free×$(15 < d < 30)$	0.024	0.014	0.015	-0.0079	0.037	0.019	-0.012	0.063
	(0.010)**	(0.0100)	(0.013)	(0.0063)	(0.020)*	(0.0098)*	(0.0099)	(0.024)**
Observations	5023118	2757521	2721271	9408441	1146664	550263	9408441	356434
Firm and Time FE	X	X	X	X	X	X	X	X
Nuts III Trends	X	X	X	X	X	X	X	X
Worker FE	X	.	X	.	.	X	.	.

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) for treated firms in the 15-30 minutes bin $I(15 < d_j \leq 30)$ weighted using the average establishment size (in FTE) as weight. While treatment is at the establishment level, the unit of observation is the single worker within an establishment. All regressions account for establishment fixed effects, period fixed effects, workers fixed effect, and linear trends per NUTS-III region. The dependent variable in column 1 is average log weekly wages for the full labor force. The dependent variable in column 2 and 3 is average log weekly wages of incumbent workers. The dependent variable in column 3 is average AKM of incumbent workers. The dependent variable in column 4 and 5 is average log weekly wages of newly hired workers. The dependent variable in column 6 is average AKM of newly hired workers. Free is a dummy from year 2004 onward. The regressions are Estimates from full sample are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

Figure 9: Value added per worker

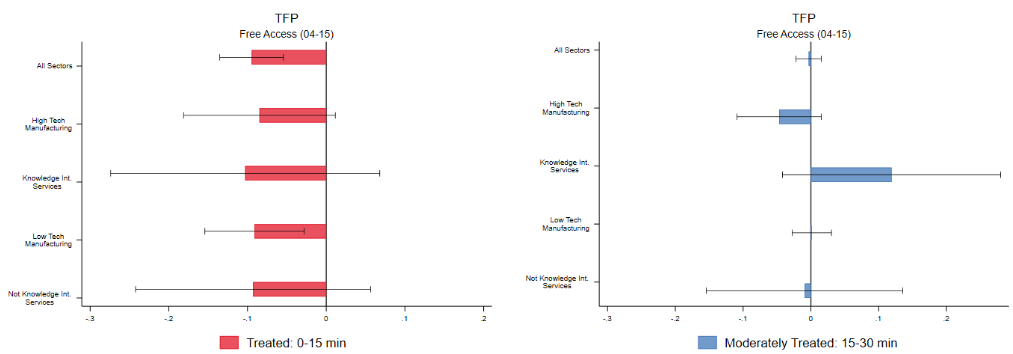
(a) Treated (0-15 min) (b) Mod. Treated (15-30 min)



Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red circles) and 15-30 min distance bin (blue triangles) of a regression based on equation (1). The coefficients report estimates for the free access phase. Panel (a) shows the effect on value added per worker in firms in the 0-15 min bin. Panel (b) on firms in the 15-30 min bin. High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. Full estimates for the transition and free access phase are reported in column (4) of Table 11 and Table 12. INPS data.

Figure 10: Total factor productivity

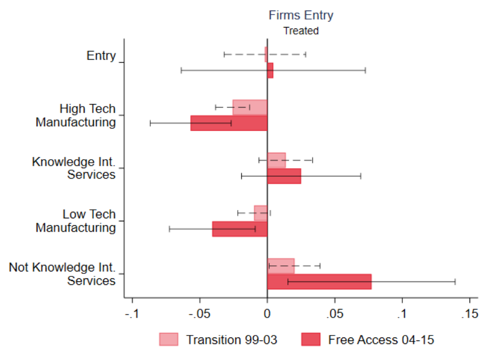
(a) Treated (0-15 min) (b) Mod. Treated (15-30 min)



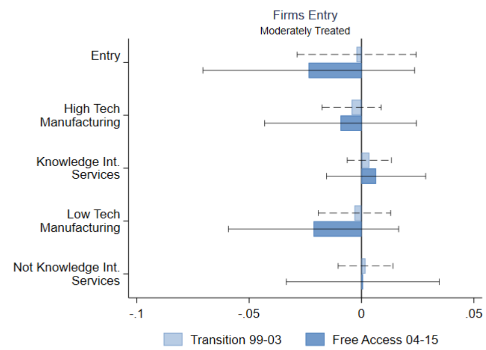
Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red circles) and 15-30 min distance bin (blue triangles) of a regression based on equation (1). The coefficients report estimates for the free access phase. Panel (a) shows the effect on TFP in firms in the 0-15 min bin. Panel (b) on firms in the 15-30 min bin. High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. Full estimates for the transition and free access phase are reported in column (4) of Table 11 and Table 12. INPS data.

Figure 11: Firm entry

(a) Treated (0-15 min)



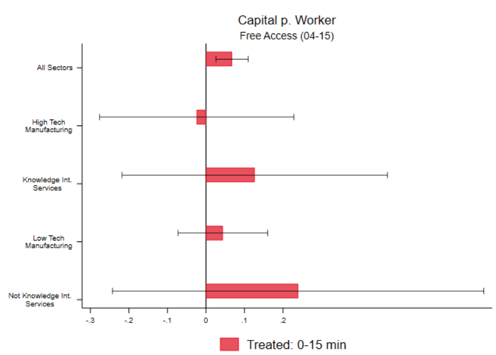
(b) Mod. Treated (15-30 min)



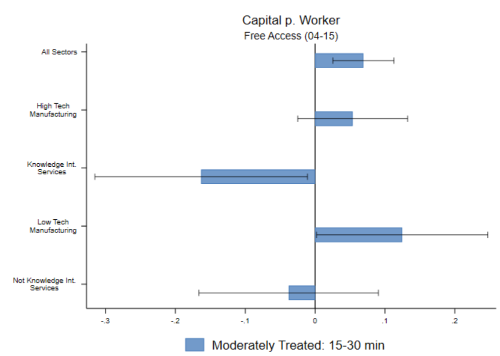
Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red circles) and 15-30 min distance bin (blue triangles) of municipality-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable s cumulated entry of firms over total number of firms in a municipality in 1998. High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 8. Panel (a) shows the effect on firms in the 0-15 min bin. Panel (b) on firms in the 15-30 min bin. Full estimates for the transition and free access phase are reported in Table 13. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

Figure 12: Capital per worker effects

(a) Treated (0-15 min)



(b) Mod. Treated (15-30 min)

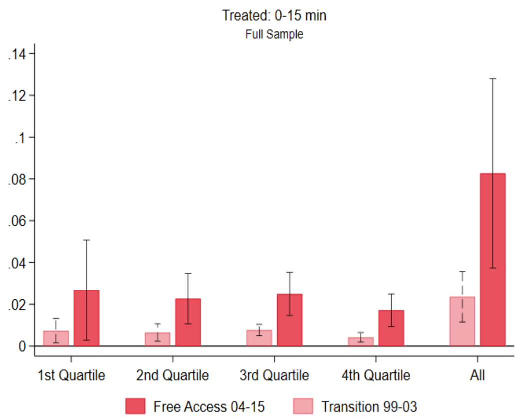


Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red circles) and 15-30 min distance bin (blue triangles) of a regression based on equation (1). The coefficients report estimates for the free access phase. Panel (a) shows the effect on value added per worker in firms in the 0-15 min bin. Panel (b) on firms in the 15-30 min bin. High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. Full estimates for the transition and free access phase are reported in column (3) of Table 11 and Table 12. INPS data.

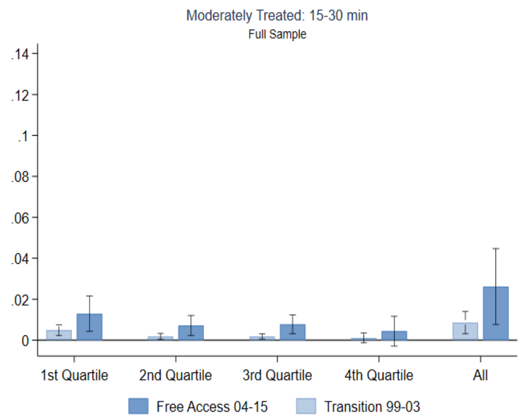
B Extra Figures and Tables

Figure 13: Exits by quartile of 98 wage distribution

(a) Treated (0-15 min)



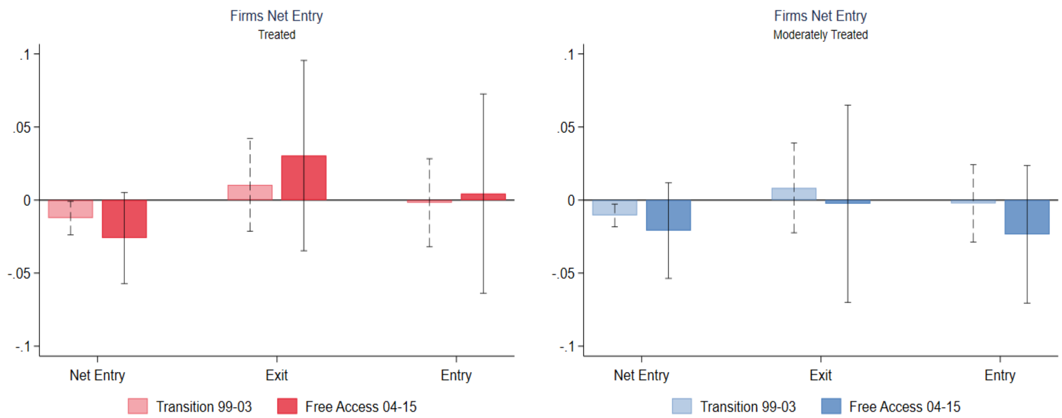
(b) Mod. Treated (15-30 min)



Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red bars) and 15-30 min distance bin (blue bars) of a regression based on equation (1) from Table 3. Standard errors are clustered by local labor market. Regression controls for firm, time and worker fixed effects. It includes NUTS III trends and a Bartik control for nationwide shifts in wages. INPS data.

Figure 14: Entry and Exit of Firms

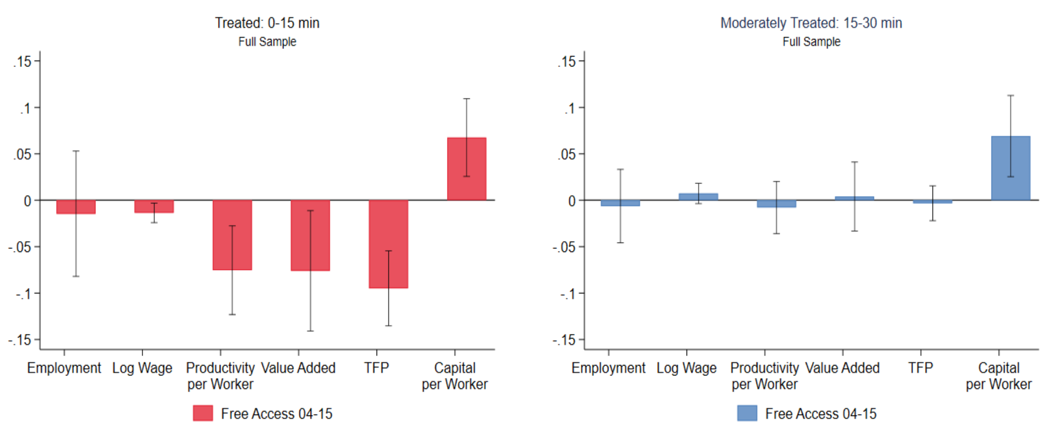
(a) Treated (0-15 min) (b) Mod. Treated (15-30 min)



Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red bars) and 15-30 min distance bin (blue bars) of a regression based on equation (1) from Table 4. Standard errors are clustered by local labor market. Regression controls for firm, time and worker fixed effects. It includes NUTS III trends and a Bartik control for nationwide shifts in wages. INPS data.

Figure 15: Margins of adjustment

(a) Treated (0-15 min) (b) Mod. Treated (15-30 min)



Notes: This figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red bars) and 15-30 min distance bin (blue bars) of a regression based on equation (1) from Table 5. Standard errors are clustered by local labor market. Regression controls for firm, time and worker fixed effects. It includes NUTS III trends and a Bartik control for nationwide shifts in wages. INPS data.

Table 8: Decomposition of Wages

	(1) Log per capita Weekly Wage	(2) Log per capita Weekly Wage	(3) Log per capita Weekly Wage Incumbent	(4) Log per capita Weekly Wage Incumbent	(5) Log per capita Weekly Wage Entrant	(6) Log per capita Weekly Wage Entrant
Transition×($d < 15$)	0.0023	0.0017	0.0034	0.0019	0.0052	-0.0033
	(0.0040)	(0.0071)	(0.0049)	(0.0062)	(0.0049)	(0.0060)
Free×($d < 15$)	-0.014	-0.0078	-0.013	-0.010	-0.028	-0.033
	(0.0054)*	(0.011)	(0.0063)	(0.0098)	(0.0100)**	(0.0099)**
Panel B: Moderately Treated						
Transition*(15<d<30)	0.0047	0.0041	0.0044	0.0034	0.0069	0.0074
	(0.0023)*	(0.0030)	(0.0014)**	(0.0028)	(0.0024)**	(0.0054)
Free*(15<d<30)	0.0073	0.0079	0.0079	0.0057	0.0061	0.0010
	(0.0055)	(0.0033)*	(0.0033)*	(0.0029)	(0.014)	(0.012)
Time FE	X	X	X	X	X	X
Nuts III trend	X	X	X	X	X	X
Worker FE	.	X	.	X	.	X
R2	0.43	0.78	0.47	0.81	0.39	0.74
F-stat	36.5	4.81	58.8	4.53	5.41	18.7
Observations	19918528	19216134	10807165	10711562	4166667	2409646

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of establishment-level DiD regressions following equation (1). While treatment is at the establishment level, the unit of observation is the single worker within an establishment. All regressions account for establishment fixed effects, period fixed effects, workers fixed effect, and linear trends per NUTS-III region. The dependent variable in column 1 and 2 is average log weekly wages for the full labor force. The dependent variable in column 3 and 4 is average log weekly wages of incumbent workers. The dependent variable in column 5 and 6 is average log weekly wages of newly hired workers. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

Table 9: Heterogeneity of Exits

	Treated				
	Exits (1)	Exits Bottom Quart (2)	Exits Lower Mid Quart (3)	Exits Upper Mid Quart (4)	Exits Top Quart (5)
			A. All Sectors		
Transition×($d < 15$)	0.024	0.0071	0.0063	0.0069	0.0053
	(0.0062)**	(0.0029)*	(0.0021)**	(0.0013)**	(0.0014)**
Free×($d < 15$)	0.083	0.026	0.021	0.023	0.021
	(0.023)**	(0.012)*	(0.0058)**	(0.0049)**	(0.0049)**
Observations	843287	843287	843287	843287	843287
			B. High-tech Manufacturing		
Transition×($d < 15$)	0.030	0.0099	0.0062	0.0086	0.0068
	(0.0081)**	(0.0031)**	(0.0018)**	(0.0025)**	(0.0021)**
Free×($d < 15$)	0.10	0.029	0.026	0.027	0.029
	(0.024)**	(0.011)*	(0.0067)**	(0.0053)**	(0.0050)**
Observations	206191	206191	206191	206191	206191
			C. Low-tech Manufacturing		
Transition×($d < 15$)	0.028	0.0096	0.0066	0.0065	0.0057
	(0.010)**	(0.0057)	(0.0029)*	(0.00097)**	(0.0012)**
Free×($d < 15$)	0.080	0.024	0.020	0.020	0.018
	(0.027)**	(0.015)	(0.0061)**	(0.0041)**	(0.0033)**
Observations	300446	300446	300446	300446	300446
			D. Knowledge Intensive Service		
Transition×($d < 15$)	-0.0024	-0.0012	-0.00060	0.0038	0.00080
	(0.015)	(0.0065)	(0.0017)	(0.0043)	(0.0097)
Free×($d < 15$)	0.038	-0.0072	-0.00088	0.020	0.018
	(0.055)	(0.011)	(0.0089)	(0.013)	(0.033)
Observations	91545	91545	91545	91545	91545
			E. Knowledge not Intensive Service		
Transition×($d < 15$)	0.017	0.0026	0.0060	0.0056	0.0036
	(0.0068)*	(0.0034)	(0.0029)	(0.0024)*	(0.0016)*
Free×($d < 15$)	0.076	0.025	0.019	0.022	0.017
	(0.026)**	(0.017)	(0.0097)	(0.0068)**	(0.0047)**
Observations	244839	244839	244839	244839	244839
Firm and Time FE	X	X	X	X	X
Nuts III Trends	X	X	X	X	X

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) from table 3 for treated firms in the 15 minutes bin $I(d_j \leq 15)$. Estimates from table 3 are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing i, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

Table 10: Heterogeneity of Exits

Moderately Treated

	Exits (1)	Exits Bottom Quart (2)	Exits Lower Mid Quart (3)	Exits Upper Mid Quart (4)	Exits Top Quart (5)
A. All Sectors					
Transition×$(15 < d < 30)$	0.0086	0.0048	0.0016	0.0017	0.0014
	(0.0028)**	(0.0013)**	(0.00067)*	(0.00065)*	(0.0012)
Free×$(15 < d < 30)$	0.026	0.013	0.0067	0.0072	0.0056
	(0.0095)*	(0.0043)**	(0.0023)**	(0.0022)**	(0.0040)
Observations	843287	843287	843287	843287	843287
B. High-tech Manufacturing					
Transition×$(15 < d < 30)$	0.0049	0.0022	0.0015	0.00089	0.00078
	(0.0030)	(0.0022)	(0.00080)	(0.00039)*	(0.00051)
Free×$(15 < d < 30)$	0.015	0.0043	0.0053	0.0046	0.0018
	(0.0093)	(0.0061)	(0.0024)*	(0.0013)**	(0.0025)
Observations	206191	206191	206191	206191	206191
C. Low-tech Manufacturing					
Transition×$(15 < d < 30)$	0.0065	0.0030	0.0013	0.0017	0.00099
	(0.0027)*	(0.0013)*	(0.00080)	(0.00046)**	(0.00072)
Free×$(15 < d < 30)$	0.018	0.0068	0.0045	0.0049	0.0038
	(0.0079)*	(0.0035)	(0.0025)	(0.0014)**	(0.0018)*
Observations	300446	300446	300446	300446	300446
D. Knowledge Intensive Service					
Transition×$(15 < d < 30)$	0.0038	0.014	-0.00075	0.00061	-0.0046
	(0.0089)	(0.0050)**	(0.0011)	(0.0028)	(0.0047)
Free×$(15 < d < 30)$	0.0034	0.026	-0.0021	0.00073	-0.0087
	(0.023)	(0.021)	(0.0036)	(0.0059)	(0.012)
Observations	91545	91545	91545	91545	91545
E. Knowledge not Intensive Service					
Transition×$(15 < d < 30)$	0.015	0.0076	0.0023	0.0021	0.0026
	(0.0049)**	(0.0025)**	(0.0015)	(0.0017)	(0.0020)
Free×$(15 < d < 30)$	0.055	0.025	0.013	0.014	0.014
	(0.017)**	(0.0095)*	(0.0036)**	(0.0050)**	(0.0073)
Observations	244839	244839	244839	244839	244839
Firm and Time FE	X	X	X	X	X
Nuts III Trends	X	X	X	X	X

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) from table 3 for treated firms in the 15-30 minutes bin $I(15 < d_j \leq 30)$. Estimates from table 3 are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing i, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

Table 11: Margins of adjustment: Heterogeneity

Strongly Treated

	Log Firm Size (1)	Average Log Wage (2)	Log Value added per capita (3)	Log Value Added (4)	TFP (5)	Log Assets per capita (6)
A. All Sectors						
Transition×($d < 15$)	-0.011	0.0023	-0.065	-0.069	-0.072	0.055
	(0.016)	(0.0040)	(0.041)	(0.034)	(0.031)*	(0.050)
Free×($d < 15$)	-0.015	-0.014	-0.075	-0.076	-0.095	0.068
	(0.034)	(0.0054)*	(0.024)**	(0.033)*	(0.021)**	(0.021)**
Observations	1111270	19918528	373190	373190	367167	387722
B. High-tech Manufacturing						
Transition×($d < 15$)	-0.036	-0.0051	-0.089	-0.094	-0.081	-0.023
	(0.023)	(0.0082)	(0.022)**	(0.039)*	(0.030)*	(0.074)
Free×($d < 15$)	-0.077	-0.011	-0.094	-0.17	-0.085	-0.024
	(0.071)	(0.011)	(0.055)	(0.12)	(0.049)	(0.13)
Observations	232639	4510278	90367	90367	89523	92248
C. Low-tech Manufacturing						
Transition×($d < 15$)	-0.016	-0.0036	-0.091	-0.063	-0.081	0.014
	(0.023)	(0.0038)	(0.042)*	(0.068)	(0.044)	(0.045)
Free×($d < 15$)	0.0063	-0.011	-0.10	-0.044	-0.091	0.044
	(0.043)	(0.011)	(0.026)**	(0.067)	(0.032)**	(0.059)
Observations	337536	5193686	99583	99583	98666	102387
D. Knowledge Intensive Service						
Transition×($d < 15$)	-0.12	0.010	-0.025	-0.20	0.0023	0.21
	(0.061)	(0.011)	(0.13)	(0.049)**	(0.072)	(0.066)**
Free×($d < 15$)	-0.12	-0.0047	-0.089	-0.30	-0.10	0.13
	(0.072)	(0.012)	(0.12)	(0.084)**	(0.087)	(0.18)
Observations	182351	4971986	58303	58303	56219	60272
E. Knowledge not Intensive Service						
Transition×($d < 15$)	0.0085	0.010	-0.038	-0.083	-0.099	0.20
	(0.026)	(0.0026)**	(0.019)	(0.065)	(0.037)*	(0.12)
Free×($d < 15$)	-0.068	0.0013	0.019	-0.081	-0.093	0.24
	(0.047)	(0.0080)	(0.069)	(0.095)	(0.076)	(0.25)
Observations	356434	5227847	124582	124582	122733	132403
Firm and Time FE	X	X	X	X	X	X
Nuts III Trends	X	X	X	X	X	X

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) from table 5 for treated firms in the 15 minutes bin $I(d_j \leq 15)$. Estimates from table 5 are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

Table 12: Margins of adjustment: Heterogeneity

Moderately Treated

	Log Firm Size (1)	Average Log Wage (2)	Log Value added per capita (3)	Log Value Added (4)	TFP (5)	Log Assets per capita (6)
A. All Sectors						
Transition×$(15 < d < 30)$	-0.016	0.0047	-0.0095	-0.035	-0.0087	0.0066
	(0.013)	(0.0023)*	(0.017)	(0.022)	(0.013)	(0.024)
Free×$(15 < d < 30)$	-0.0064	0.0073	-0.0077	0.0041	-0.0033	0.069
	(0.020)	(0.0055)	(0.014)	(0.019)	(0.0096)	(0.022)**
Observations	1111270	19918528	373190	373190	367167	387722
B. High-tech Manufacturing						
Transition×$(15 < d < 30)$	0.013	0.0047	-0.015	-0.025	0.0079	-0.059
	(0.032)	(0.0027)	(0.029)	(0.054)	(0.028)	(0.049)
Free×$(15 < d < 30)$	0.028	0.011	-0.074	-0.068	-0.047	0.054
	(0.052)	(0.0061)	(0.041)	(0.049)	(0.032)	(0.040)
Observations	232639	4510278	90367	90367	89523	92248
C. Low-tech Manufacturing						
Transition×$(15 < d < 30)$	-0.047	0.0018	0.0063	-0.035	-0.0045	0.057
	(0.019)*	(0.0034)	(0.018)	(0.046)	(0.021)	(0.033)
Free×$(15 < d < 30)$	-0.054	0.0096	0.0083	0.0079	0.0014	0.12
	(0.043)	(0.0053)	(0.016)	(0.031)	(0.015)	(0.063)
Observations	337536	5193686	99583	99583	98666	102387
D. Knowledge Intensive Service						
Transition×$(15 < d < 30)$	-0.026	-0.0077	-0.15	-0.10	-0.018	-0.033
	(0.062)	(0.0083)	(0.12)	(0.062)	(0.070)	(0.057)
Free×$(15 < d < 30)$	-0.022	-0.014	-0.0016	0.0036	0.12	-0.16
	(0.11)	(0.010)	(0.13)	(0.061)	(0.082)	(0.078)*
Observations	182351	4971986	58303	58303	56219	60272
E. Knowledge not Intensive Service						
Transition×$(15 < d < 30)$	0.0049	0.010	-0.023	-0.099	-0.066	-0.041
	(0.019)	(0.0038)*	(0.061)	(0.068)	(0.059)	(0.032)
Free×$(15 < d < 30)$	0.0030	0.025	0.034	-0.018	-0.0093	-0.038
	(0.030)	(0.0091)*	(0.11)	(0.070)	(0.074)	(0.066)
Observations	356434	5227847	124582	124582	122733	132403
Firm and Time FE	X	X	X	X	X	X
Nuts III Trends	X	X	X	X	X	X

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) from table 5 for moderately treated firms in the 15-30 minutes bin $I(15 < d_j \leq 30)$. Estimates from table 5 are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

Table 13: Share Firms Entry

	(1) Entry All Sectors	(2) Entry High Tech Manufacturing	(3) Entry Knowledge Intensive Services	(4) Entry Low Tech Manufacturing	(5) Entry Not Knowledge Intensive Services
Panel A: Treated					
Transition×($d < 15$)	-0.0020	-0.026	0.014	-0.010	0.020
	(0.015)	(0.0064)**	(0.010)	(0.0061)	(0.0096)*
Free×($d < 15$)	0.0042	-0.057	0.025	-0.041	0.077
	(0.035)	(0.015)**	(0.023)	(0.016)*	(0.032)*
Relative Effect	0.014	-0.83	0.81	-0.33	0.97
Panel B: Moderately Treated					
Transition×($15 < d < 30$)	-0.0024	-0.0044	0.0034	-0.0034	0.0018
	(0.013)	(0.0067)	(0.0050)	(0.0081)	(0.0062)
Free×($15 < d < 30$)	-0.024	-0.0093	0.0065	-0.022	0.00065
	(0.024)	(0.017)	(0.011)	(0.019)	(0.017)
Relative Effect	-0.079	-0.14	0.21	-0.18	0.0082
Mean of Dep. Var.	**0.30**	**0.068**	**0.031**	**0.12**	**0.079**
Firm FE	X	X	X	X	X
Time FE	X	X	X	X	X
Nuts III trend	X	X	X	X	X
R2	0.94	0.88	0.88	0.90	0.87
F-stat	5.48	12.3	8.48	8.77	6.04
Observations	13740	13740	13740	13740	13740

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of municipality-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is cumulated entry of firms over total number of firms in a municipality in 1998. Columns 2-5 restrict the sample to specific industries: High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

Table 14: Share Firms Exit

	(1) Exit All Sectors	(2) Exit High Tech Manufacturing	(3) Exit Knowledge Intensive Services	(4) Exit Low Tech Manufacturing	(5) Exit Not Knowledge Intensive Services
			Panel A: Treated		
Transition×($d < 15$)	0.010	-0.016	0.015	-0.018	0.029
	(0.016)	(0.0064)*	(0.014)	(0.014)	(0.013)*
Free×($d < 15$)	0.030	-0.046	0.030	-0.056	0.10
	(0.033)	(0.017)*	(0.031)	(0.036)	(0.035)**
Relative Effect	0.15	-1.05	2.35	-0.58	2.30
			Panel B: Moderately Treated		
Transition×($15 < d < 30$)	0.0083	0.0012	0.0019	-0.0058	0.011
	(0.016)	(0.0059)	(0.0040)	(0.0100)	(0.0083)
Free×($15 < d < 30$)	-0.0026	-0.0041	0.0036	-0.023	0.021
	(0.034)	(0.019)	(0.011)	(0.024)	(0.022)
Relative Effect	-0.013	-0.093	0.28	-0.24	0.47
Mean of Dep. Var.	**0.20**	**0.044**	**0.013**	**0.098**	**0.045**
Firm FE	X	X	X	X	X
Time FE	X	X	X	X	X
Nuts III trend	X	X	X	X	X
R2	0.96	0.90	0.85	0.91	0.88
F-stat	13.8	9.52	4.63	2.41	14.5
Observations	13740	13740	13740	13740	13740

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of municipality-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is cumulated exits of firms over total number of firms in a municipality in 1998. Columns 2-5 restrict the sample to specific industries: High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

Table 15: Share Firms Net Entry

	(1) Net Entry All Sectors	(2) Net Entry High Tech Manufacturing	(3) Net Entry Knowledge Intensive Services	(4) Net Entry Low Tech Manufacturing	(5) Net Entry Not Knowledge Intensive Services
			Panel A: Treated		
Transition×($d < 15$)	-0.012	-0.0098	-0.0017	0.0085	-0.0093
	(0.0059)*	(0.0028)**	(0.0042)	(0.011)	(0.0054)
Free×($d < 15$)	-0.026	-0.010	-0.0050	0.015	-0.026
	(0.016)	(0.0068)	(0.0096)	(0.023)	(0.0082)**
Relative Effect	-0.26	-0.43	-0.28	0.61	-0.76
			Panel B: Moderately Treated		
Transition×($15 < d < 30$)	-0.011	-0.0056	0.0015	0.0025	-0.0092
	(0.0041)*	(0.0020)**	(0.0019)	(0.0031)	(0.0028)**
Free×($15 < d < 30$)	-0.021	-0.0051	0.0029	0.0017	-0.021
	(0.017)	(0.0025)*	(0.0033)	(0.0078)	(0.0083)*
Relative Effect	-0.21	-0.21	0.16	0.068	-0.60
Mean of Dep. Var.	**0.10**	**0.024**	**0.018**	**0.025**	**0.034**
Firm FE	X	X	X	X	X
Time FE	X	X	X	X	X
Nuts III trend	X	X	X	X	X
R2	0.77	0.77	0.70	0.76	0.63
F-stat	2.93	5.96	0.83	1.53	14.0
Observations	13740	13740	13740	13740	13740

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of municipality-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is cumulated net entry of firms over total number of firms in a municipality in 1998. Cumulated net entry is defined as number of new firms minus number of firms who exit cumulated over the years. Columns 2-5 restrict the sample to specific industries. High-tech manufacturing, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

Table 16: Labor force composition: Heterogeneity

Strongly Treated

	Share Part-Time 1998 Size (1)	Median Age (2)	Average Experience (3)	Share Women 1998 Size (4)	Share Foreigners 1998 Size (5)
A. All Sectors					
Transition×$(d < 15)$	0.0047	-0.0032	-0.020	0.015	-0.0022
	(0.0033)	(0.0018)	(0.016)	(0.0090)	(0.0031)
Free×$(d < 15)$	0.0090	-0.0057	-0.039	0.021	0.0065
	(0.0096)	(0.0049)	(0.020)	(0.014)	(0.012)
Observations	1111270	1111270	1111270	1111270	1111270
B. High-tech Manufacturing					
Transition×$(d < 15)$	-0.0011	0.00013	0.0076	-0.0088	-0.0039
	(0.0035)	(0.0068)	(0.021)	(0.0083)	(0.0037)
Free×$(d < 15)$	0.0094	0.0099	-0.021	0.0036	0.013
	(0.017)	(0.015)	(0.017)	(0.024)	(0.0092)
Observations	232639	232639	232639	232639	232639
C. Low-tech Manufacturing					
Transition×$(d < 15)$	0.0033	-0.0043	-0.015	0.0079	-0.0034
	(0.0018)	(0.0035)	(0.015)	(0.0058)	(0.0052)
Free×$(d < 15)$	0.00068	-0.0098	-0.026	0.028	-0.0071
	(0.0016)	(0.0025)**	(0.024)	(0.011)*	(0.014)
Observations	337536	337536	337536	337536	337536
D. Knowledge Intensive Service					
Transition×$(d < 15)$	0.0065	-0.0025	-0.013	-0.030	0.0029
	(0.019)	(0.0059)	(0.023)	(0.028)	(0.0093)
Free×$(d < 15)$	-0.046	0.0048	-0.0072	-0.10	0.021
	(0.046)	(0.0074)	(0.030)	(0.055)	(0.034)
Observations	182351	182351	182351	182351	182351
E. Knowledge not Intensive Service					
Transition×$(d < 15)$	-0.00036	-0.0086	-0.029	0.026	-0.00052
	(0.0068)	(0.0037)*	(0.014)	(0.012)*	(0.0068)
Free×$(d < 15)$	0.00017	-0.015	-0.049	-0.0048	0.011
	(0.016)	(0.0098)	(0.018)*	(0.014)	(0.011)
Observations	356434	356434	356434	356434	356434
Firm and Time FE	X	X	X	X	X
Nuts III Trends	X	X	X	X	X

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) for treated firms in the 15 minutes bin $I(d_j \leq 15)$. The dependent variable in column 1 is log age of the median worker. The dependent variable in column 2 is average log experience of workers. The dependent variable in column 3 is share of women on total employment in 1998. The dependent variable in column 4 is share of foreigners on total employment in 1998. The dependent variable in column 5 is cumulated workers' promotions on total employment in 1998. Estimates for the full sample are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing i, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

Table 17: Labor force composition: Heterogeneity

Moderately Treated

	Share Part-Time 1998 Size (1)	Median Age (2)	Average Experience (3)	Share Women 1998 Size (4)	Share Foreigners 1998 Size (5)
A. All Sectors					
Transition×$(15 < d < 30)$	0.0093	0.0026	-0.0076	0.0081	-0.00023
	(0.0016)**	(0.0018)	(0.0051)	(0.0040)	(0.0020)
Free×$(15 < d < 30)$	0.019	0.0025	-0.017	0.019	0.0067
	(0.0040)**	(0.0033)	(0.0087)	(0.0085)*	(0.0052)
Observations	1111270	1111270	1111270	1111270	1111270
B. High-tech Manufacturing					
Transition×$(15 < d < 30)$	0.00018	0.0048	0.0060	-0.0055	-0.00075
	(0.00061)	(0.0031)	(0.0076)	(0.0077)	(0.0050)
Free×$(15 < d < 30)$	0.0073	0.0098	0.010	0.0012	-0.0057
	(0.0023)**	(0.0080)	(0.0062)	(0.015)	(0.0043)
Observations	232639	232639	232639	232639	232639
C. Low-tech Manufacturing					
Transition×$(15 < d < 30)$	0.0037	0.0026	-0.00030	0.0026	-0.0041
	(0.0019)	(0.0038)	(0.0035)	(0.0054)	(0.0025)
Free×$(15 < d < 30)$	0.0072	0.0010	-0.012	0.015	-0.0020
	(0.0019)**	(0.0048)	(0.0061)	(0.0099)	(0.0048)
Observations	337536	337536	337536	337536	337536
D. Knowledge Intensive Service					
Transition×$(15 < d < 30)$	0.030	-0.0018	-0.010	0.0058	-0.0016
	(0.030)	(0.0081)	(0.012)	(0.055)	(0.011)
Free×$(15 < d < 30)$	0.012	-0.0071	-0.0093	-0.039	0.0034
	(0.056)	(0.013)	(0.014)	(0.097)	(0.020)
Observations	182351	182351	182351	182351	182351
E. Knowledge not Intensive Service					
Transition×$(15 < d < 30)$	0.015	-0.0019	-0.018	0.021	0.0072
	(0.0092)	(0.0044)	(0.011)	(0.022)	(0.0028)*
Free×$(15 < d < 30)$	0.038	-0.0029	-0.023	0.029	0.029
	(0.025)	(0.010)	(0.020)	(0.018)	(0.0089)**
Observations	356434	356434	356434	356434	356434
Firm and Time FE	X	X	X	X	X
Nuts III Trends	X	X	X	X	X

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents heterogeneity results of establishment-level DiD regressions following equation (1) for moderately treated firms in the 15-30 minutes bin $I(15 < d_j \leq 30)$. The dependent variable in column 1 is log age of the median worker. The dependent variable in column 2 is average log experience of workers. The dependent variable in column 3 is share of women on total employment in 1998. The dependent variable in column 4 is share of foreigners on total employment in 1998. The dependent variable in column 5 is cumulated workers' promotions on total employment in 1998. Estimates for the full sample are reported in Panel A. Each following panel restricts the sample to specific industries: High-tech manufacturing i, Low-tech manufacturers, Knowledge-intensive services, Not knowledge-intensive services as defined in Figure 7. INPS data.

C Reforms and Data

C.1 Labor market integration

Agreement of the Free Movement of Persons (AFMP) I briefly outline here the main features of the AFMP focusing on the peculiarities with respect to the Italian labor market. A detailed discussion of the reform is available in Beerli et al. (2018).[90] The AFMP agreement provided free worker mobility among the EU and Switzerland. It was signed in 1999, passed a national referendum in 2000, and was enacted starting in 2002. Table 18 highlights the main features of the reform. Anticipatory effects were possible from 1999, when the details of the agreement were made public. Before 1998, in the *Pre-Treatment* phase, both resident immigrants and cross border workers were subject to national quotas set by the federal government. In the *Transition* phase, starting from 1999, cantonal offices started handling job applications of cross borders in a less stringent way. Also, the previous requirement of a 6th months residence in a bordering region in Italy was no longer necessary. Cross border workers permits' duration was extended to 5 year in 2002. Before than, the maximum duration was one year and the permit was tied to a specific job. Finally, weekly instead of daily commuting was allowed.[91] In 2004 the agreement was fully implemented starting the *Free* phase with the abolition of the so called "priority requirement". In practice, Swiss employers where no longer required to prove they could not find an equally suitable Swiss worker to fill their vacancy. Also, cross borders were granted access to every Swiss region, and not just the bordering ones. The requirements for permanent resident immigrants did not change much around these dates. Higher quotas were implemented, but the labor market for resident immigrants was fully liberalized in 2007.

Table 18: Implementation timeline of the AFMP

Phase	Year	Event	Rules: CBW	Rules: Resident Immigrants
Pre-Treatment	Pre 1998		Full Restrictions	Full Restrictions
	1998	Agreement announced		
Transition	1999	Agreement signed	More "relaxed" handling of permit applications	
	2000	Referendum	CBW permit duration 1 year - stops with contract	
			No requirem. of 6 months residence in border region	
	2002	Agreement enacted	CBW permit duration 5 years	Higher quotas
			Weekly commuting	
Full Liberalization	2004	First liberalization	No priority requirement.	Abolition admission process
	2007	Full liberalization	Full access to all regions	No restrictions
	2008	Schengen area	No controls at the border	

Notes: Table adapted from (Beerli and Peri, 2015)

[90] And also extensively in Ruffner and Siegenthaler (2017).

[91] Though the vast majority of cross borders was still commuting every day (Beerli and Peri, 2015).

Table 19: Agreements between Switzerland and the EU

Agreement	Description	Effect
Free Movement of Persons	Free access to labor market	Expansion of local labor markets
Mutual Recognition	lower administrative costs for approval of products for some manufacturing sectors	Cost savings of 0.5 –1 % of product value per year. Corresponds to less than 0.2% of trade volume between EU and Switzerland. Increased mostly imports to Switzerland at the intensive margin
Land Traffic	Higher weight limit on carriages, tax on alp-crossing transport	By 2006, accumulated reduction in cost for transports between Switzerland and EU of 8.3%
Air Traffic	More competitive pressure for air-lines	More and cheaper connections from Geneva Airport
Public Procurement	Swiss purchasers (municipalities, utilities, rail, airports, local traffic) need to tender internationally	Unknown (10% of bidders for municipal purchases were foreign)

Other agreements The signing of the AFMP was part of a bundle of agreements between Switzerland and the EU which were all ratified around 2002. Table 19 provides an overview of these agreements.[92] I briefly summarize here the most relevant implications for my setting. The most relevant agreements where the Mutual Recognition Agreement(MRA) and the Land Traffic Agreement (LTA). The first one introduced lower administrative costs for approving products of specific manufacturing sectors. This basically increased the volume of trade between EU, and therefore Italy, and Switzerland; while it is surely possible that this reform might confound the main effect of enacting the AFMP, I can rule this out focusing on industries which were not included in this agreement. The LTA instead, increased the higher weight limit that was allowed to be transported in Switzerland. The Swiss statistical office estimated an accumulated reduction in costs of around 8.3% which is unlikely to confound my estimates. Also in this case is it possible for me to exclude tradable industries from my estimates. Finally, the public procurement agreement's effect in my setting are quite unknown and difficult to estimate. However, given the peculiarity of such kind of contracts, is it reasonable to assume they are not the main driver of my results. I did not report the agreement on agricultural sector as I exclude that sector from my analysis, and the agreement on research cooperation which does not affect private sector firms.

The Italian Labor Market According to the Italian legislation wages are set at two levels. First, at a national-industry level, and second, at a company level. Such regulations in the labor market have been constant throughout the analysis period. From 2011 some regulation have been implemented to support company bargaining. Anyway companies are not allowed to set wages at a lower level than the national bargained one. Though these reforms aimed at supporting

[92] An extensive discussion of these reforms and their effects can be found in (Hafner, 2019) and (Beerli et al., 2018)

company bargaining, the vast majority of Italian contracts still follows the nationwide industry-level agreements. Also, the main regulations on employment protection and social security did not have mayor changes from 1993 up to 2010. In 2012 new social security measures where introduced to help workers who lost their jobs due to the crisis. In 2015 the so called "jobs act" introduced more flexibility in the labor market. All of these measures where uniform across the whole Italian labor market. Some of them were more generous for workers and firms in the south, but they all uniformly affected the firms and workers in my sample.

C.2 Data sources and construction

The following paragraphs features an overview of all the data sets and describe the construction of variables. INPS data have been available through the VisitInps Scholar type B program.

INPS Data: Workers Italian Social Security data provides individual workers' contribution histories for the universe of Italian private sector's employees. The data are reported from employers who provide the institute with information about their employees when paying mandatory contributions of their workers. The relevant data set is *rapporti di lavoro annuali*. This is a yearly panel where each worker has a record for each employment relationship in that year. For each record, the following information is available. Employer's id, start of contract, end of contract*, reason for termination*, part-time employment, share of part-time work, number of total weeks worked, number of actual weeks paid, gross income for contribution basis, extra income not subject to contributions*, months of employment, qualification, municipality of work*.[93] This information is coupled with time invariant demographics available in *anagrafica*: municipality of last residence and birth, gender, date of death, date of retirement, citizenship.

- *Sample restrictions*: I keep all workers aged between 16 and 65 with at least one employment spell between 1994 and 2015.
- *Full time equivalent employment*: I use the part-time share to define full time equivalent employment. Therefore, an employee who works at 80% accounts for 0.8 workers. Alternatively, I assign every part-time worker a share of 50%, or I define the dimension of the firm using the number of employees reported by the employer. These numbers are all very similar and do not change my results. I measure employment in weeks, as this is the most reliable information available. Months are flagged as well, but a full month is flagged even for one week

[93]* Available form 2005

of work. The information on days is not as reliable either, as it includes extra days paid but not actually worked. Weeks instead are already reported in terms of weeks at work and weeks paid, already accounting for the share of part time work.

- *Weekly wages*: wages are reported as yearly income. I use both the contribution basis and the total income including transfers and additional payments. I deflate them using the consumer price index at 2015 constant prices. I then divide these two measure by the number of weeks paid to get the amount of real weekly wages. I winsor wages at 0.05 and 99.5 percentile.

- *Employment transitions*: From the yearly panel, I flag as hiring the first spell at a new employer during the employee's history. In the same spirit, I define the last spell as a separation. I flag a separation as a job to job transition any time I observe the worker at a new employer in the same year or the year afterwards. I flag as promotion any time I observe two identical records for the same worker at the same employer but with a higher qualification.

- *Exit from INPS data*: I flag as *exit* from INPS data any separation of workers where I do not observe a pension spell or a death. This "exit" could be because of a worker moving to the public sector, to self-employment, becoming an external collaborator, or leaving Italy. Using a sample of public sector employees and self employed workers, I shut down the *exit* label any time I observe a worker in one of these samples. However, becoming a self employed or an external collaborator does not rule out by definition the possibility that the worker moved abroad. Therefore, my estimate of individuals moving abroad is likely to be conservative.

- *Distance to the border*: I match each municipality of residence and work with the distance data set using *codice catastale*. I assign to each worker the driving, time, and air distance from it's residence and job municipality to the closest Swiss border crossing.

INPS Data: Firms The relevant firm datasets for firms are *aziende annuali* and *anagrafica aziende*. From these I build a yearly panel of establishments featuring information on firm id, group id, legal type of firm, date of opening and closure, reason for closure, 4 digit NACE sector, number of employees, full amount of wages paid to all employees and managers, firm municipality.

- *Size requirement*: I restrict the sample to firms that are always smaller than 3 FTE employees or bigger than 250 FTE employees. This cuts roughly 50% of firms on the left tail and fewer than 0.5% on the right one. The main sample consist of firms with at least 3 FTE employees within one year, who are active in 1998.

- *Border assignment*: I merge the municipality of the firm with my distances data set. Then I exclude firms further away then 75 minutes or 75 km driving distance from the Swiss border. This excludes now 90% of observations

- *Firms and workers in Milan*: I exclude all firms in Milan, all firms in Campione d'Italia, and all firms where the entire labor force lives in Milan. This is the case for some firms whose legal headquarter is placed outside of Milan, but the actual establishments are in Milan. Also, Milan has a way more mobile labor market, and it is located at 50 minutes from the border. Milan would therefore be assigned to the control group. However, looking at the pattern of *exits*, Milan is clearly an outlier with more than 80'000 workers disappearing from social security data over 10 years. This excludes 93.5% of observations.

- *Sectors*: I exclude firms with missing sector and firms operating in agriculture, in the public sector, and international organizations. Also, I drop firms owned by public institutions, by the church, or by political parties excluding now 94.1% of the sample

Excluding firms because of the size leaves me with 42% of Italian employment between 1994 and 2015. Among these firms, eligible firms for my analysis represent 12% of employment, or 5.8% the total Italian employment in the same period. Table 20 offers an overview of the characteristics of Italian firms compared to my sample. Overall, more than 853'000 firms have at least 3 FTE employees in one year and are active between 1994 and 2015. Column (1) shows all firms. Column (4) includes all Italian firms who reached a size of 3 FTE employees. Column (3) and (4) divide them between eligible and not eligible firms for my sample.

Cerved Data Cerved data provide balance sheets' information for Italian incorporated firms. Data are available from 1996 to 2016. The variables are merged at the firm level. 95% of firms have a single establishment in one year. Firms with multiple establishments over the analysis period are excluded from the analysis of firms' outcomes. I use the following variables: value of tangible assets, value of intangible assets, depreciation, value added, value of production, revenues, profits, total assets, and labor costs. Employment is merged directly form the INPS data. I therefore compute labor productivity as value added per employee and total factor productivity following Wooldridge (2009) and Levinsohn and Petrin (2003). All nominal values are deflated using sector specific GDP deflators to 2015 values.

Table 20: Characteristics of Italian firms vs. working sample

	(1) All Firms 1998 All sizes	(2) All firms 1998 3-250	(3) Not Eligible 1998 3-250	(4) Final Sample 1998 3-250
Firm				
FTE Employees	10.6	13.0	12.9	14.3
	[102.9]	[21.4]	[21.1]	[23.5]
Number of New Workers	3.60	4.32	4.40	3.61
	[92.7]	[9.70]	[9.73]	[9.47]
Share of Part-Time Workers	0.13	0.094	0.095	0.080
Share of Blue Collars	0.70	0.71	0.71	0.67
Firm Age in 1998	10.9	11.8	11.6	12.9
	[9.28]	[9.43]	[9.39]	[9.74]
Primary Sector	0.011	0.012	0.013	0
Secondary Sector (Manufacturing)	0.30	0.35	0.34	0.48
Tertiary Sector (Service)	0.69	0.64	0.65	0.52
Eligible Firm	0.065	0.097	0	1
Number of obs	853262	569972	514811	55161

Notes: Average characteristics of Italian firms. Column (1) averages across all Italian firms in 1998. Column (2) restricts to firms between 2 and 250 FTE employees. Column (3) and (4) splits firms in column (2) into firms not eligible (3) and eligible (4) for my analysis. INPS data.

Swiss Data Swiss Social Security data are provided by the Swiss Statistical Office. Like in the INPS data, I am able to observe complete workers' history and demographics characteristics of Swiss workers. I mostly rely on ZEMIS, a data set containing employment spells of immigrants working in Switzerland. I exploit the nationality of immigrants and their resident permit. In particular, I can distinguish between resident immigrants and cross border workers. For the latter category, I have information on the municipality of residence in the country of origin. I couple this information with my Italian data. Yearly information on immigrants is available from 2003. From that year on I can observe every immigrant's spell. For the previous years however, I have information on cross border workers who keep working until 2003. This means that, for the early years in my analysis I only observe a subset of long term cross border workers. Appendix D describes the Swiss data set and summarizes characteristics of Italian cross borders in Switzerland

D Characteristics of Italian Cross Border Workers

Italians are the second largest group of working immigrants in Switzerland as shown in figure 16a. More than 300'000 Italians currently work in Switzerland, and almost one third of them does so as a cross border worker. The total number has been constantly increasing since 1990, when Italians working in Switzerland were around 150'000. The biggest immigration inflow of residents and cross borders took place after 2000, 2004, and 2007, in line with the liberalization process of the market access. This is shown in figure 16c.[94] Figure 16d decomposes the inflow of cross borders into high versus low skilled occupations. The number of cross borders increased from 20'000 to almost 80'000 in 25 years. Among them, the number of low shilled workers had almost a fourfold increase from 18'000 in 1990 to 56'000. The number of cross borders in a high skilled occupation instead, increased more than 10 times: from 2'000 to 24'000 today.

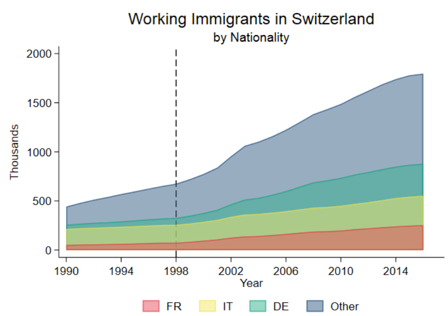
Table 21 reports summary characteristics of Italian workers in Switzerland as observed in their first employment spell (except wage and number of spells, which are averages of their employment history in Switzerland). Cross borders are almost ten years younger than resident immigrants. The average cross border has been employed for 14 years, 10 years less than the average resident immigrant. Women represent 38% of all workers. Resident immigrants are more likely to work in a skilled occupation or in a skilled sector. While 92% of cross borders works in Ticino (and 99% of them in a bordering canton) only 21% of Residents work in the same bordering regions. Jobs in Switzerland are quite stable for Italians, and the average worker changes fewer than two employers while working in Switzerland. The average wage of a cross border is 4'200 Swiss francs. Residents are slightly better paid with an average wage of 4'850 Swiss francs. High skill occupations offer, on average, much higher salaries (around 6'000 for cross borders and 8'000 for residents) than low skilled occupations (3'800 for cross borders and 4'800 for residents). The average cross border lives 17 minutes away to the nearest border crossing. The vast majority of cross borders (79%) lives within 30 minutes to the border, and 88% of them lives within 30 kilometers to the border. Figure 17 ranks municipalities on the x axis, according to their driving distance to the Swiss border in five minutes bins. Panel (a) shows the absolute number of cross borders in each municipality bin, while panel (b) shows the dame figure as share of 1991 population in the same municipalities. Each line is for a different sample year from 1994 to 2007 [95] According to the graphs, in municipalities within

[94]The figure shows a spike in 2003, this is because, for the flows before that date, I have only data on workers who are still employed in Switzerland in 2003. One can nevertheless see the increase in the number of stayers after 1998.

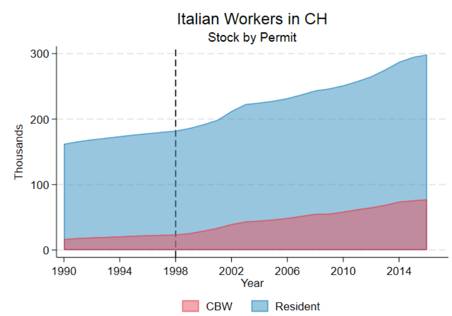
[95]The time horizon stops in 2007 as I do not have access to municipality of residence for cross borders in the years

Figure 16: Characteristics of working immigrants in Switzerland

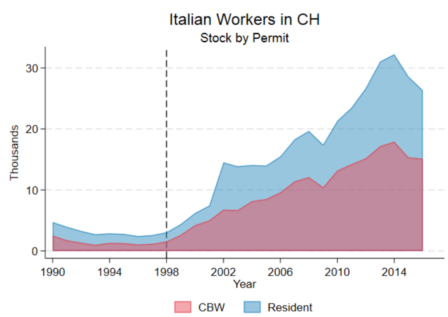
(a) Workers by Nationality



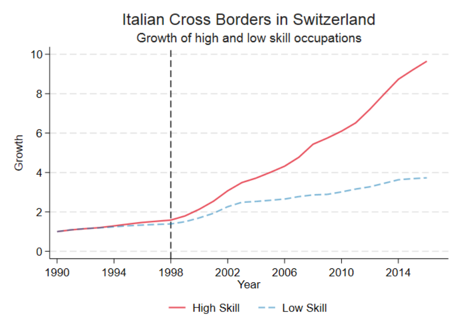
(b) Stock of RI and CBW



(c) Flow of RI and CBW



(d) High vs. Low Skilled

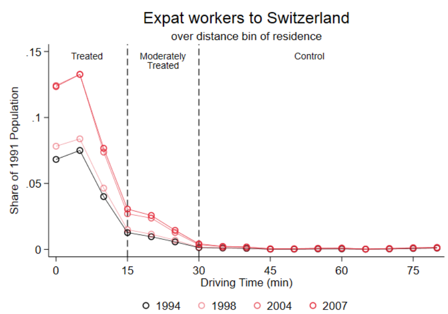


Notes: Panel (a) stock of immigrants in Switzerland by nationality. Panel (b) stock of Italians in Switzerland by resident permit (Resident immigrant or cross border worker). Panel (c) flow of Italians by resident permit. Panel (d) relative increase of cross border workers in high vs. low skilled occupations. High skill occupations are managers, scientific occupations, and technical occupations ISCO code 1, 2, and 3. All data are from own calculations based on ZEMIS data.

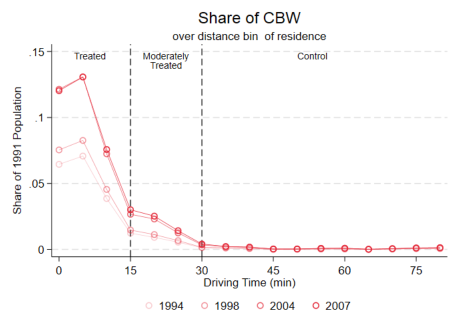
15 minutes of commuting time to Switzerland, 3 to 15% of the population works as cross borders. This number floats around 1 and 3% for municipalities between 15 and 30 minutes of driving time to Switzerland. The share of the population working as cross border in municipalities further away than 30 minutes is instead indistinguishable from zero.[96]

Figure 17: Expat workers by distance bin of the municipality of residence

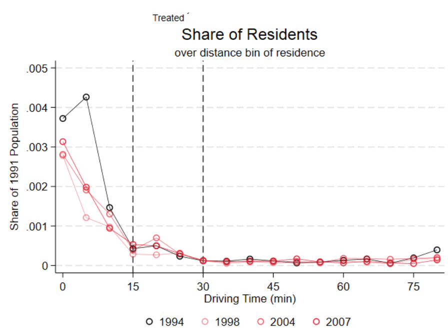
(a) Expat workers



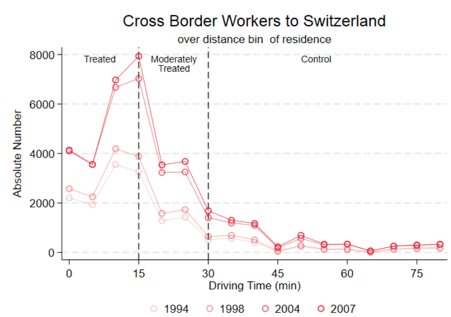
(b) Cross borders



(c) Resident immigrants



(d) Cross borders: absolute



Notes: Expat workers per municipality. Municipalities are ranked on the x axis according to the driving distance to the Swiss border and grouped within five minutes bins. Panel (a) shows the number of expat workers as share of 1991 population in the municipalities. Panel (b) shows the share of cross borders and pane (c) the share of residents. Panel (d) shows the absolute number of cross borders. Each line is for a different sample year from 1994 to 2007.

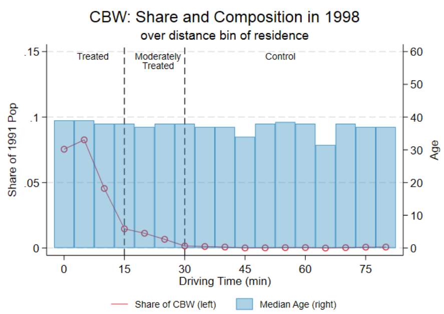
Figure 18 displays the share of cross borders in each municipality bin, together with average characteristics of workers in each bin. Each panel shows there is no particular selection of immigrants across distance bins in terms of age, gender, occupation, sector, place of work, and average wages.

after 2007.

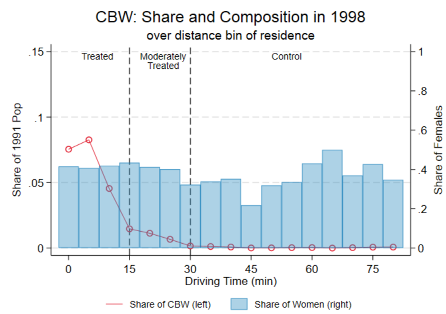
[96]It would be more appropriate to show the number of cross borders as share of the labor force in the same municipalities. However, as residence is not time variant in the Italian data, I cannot construct a consistent picture over time. When I measure cross borders as share of the labor force in 2017 (the only year for which residence information is available, I find that cross borders are 60 to 80% of the Italian labor force in treated municipalities. The same number is around 30 to 10% in moderately treated municipalities, and again zero for municipalities in the control group.

Figure 18: Share of cross borders on Italian population by distance bin

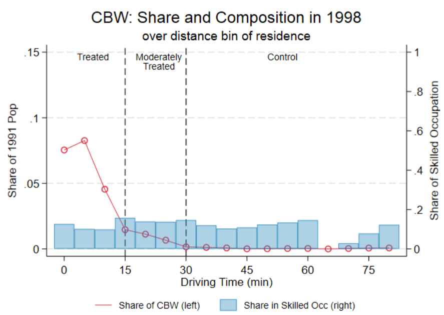
(a) Age



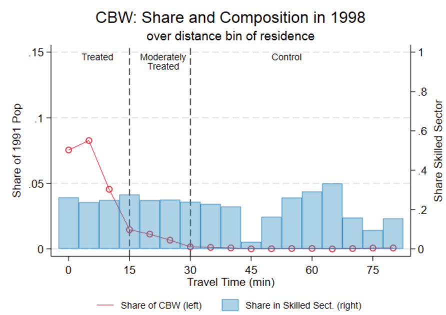
(b) Women



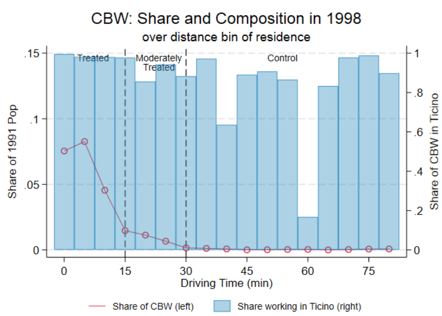
(c) High skilled occup.



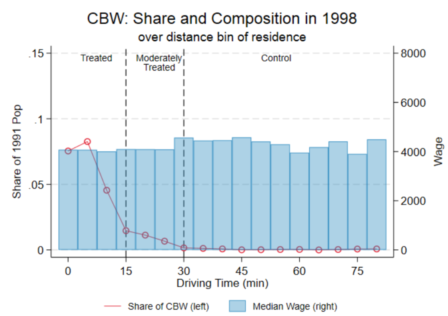
(d) High skilled sect.



(e) Works in Ticino



(f) Average wages



Notes: This figure shows again the share of Cross Border Workers per municipality on population in 1991. Each panel adds a different characteristic of cross borders in each distance bin. Panel (a) shows average age, panel (b) gender, panel (c) share of workers in a high skill occupation, panel (d) share of workers in a high skilled sector, panel (e) share of workers in Ticino, and panel (f) average wages.

Table 21: Italians working in CH

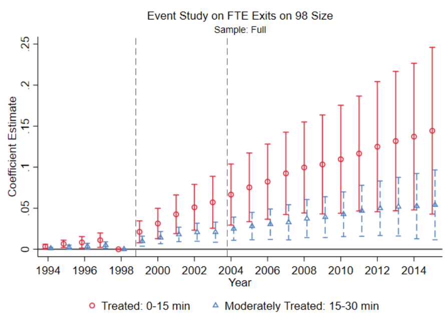
	(1) Full	(2) CBW	(3) RM
Panel A: Worker Characteristics			
Age	46.2	38.9	47.9
	[14.2]	[10.7]	[14.4]
Female	0.38	0.38	0.38
Years since in CH	21.4	13.9	23.1
	[7.63]	[8.32]	[6.29]
Panel B: Job Characteristics			
Skilled occupation	0.24	0.21	0.26
High skill intensive sector	0.29	0.28	0.35
Works in Ticino	0.25	0.92	0.16
Works in bordering canton	0.31	0.99	0.21
Job spells	1.21	1.79	1.07
	[0.96]	[1.64]	[0.64]
Job duration (months)	424.3	157.8	487.1
	[227.2]	[122.7]	[198.8]
Wage (thousands)	4.72	4.20	4.85
	[4.88]	[3.65]	[5.13]
Wage high skilled (thousands)	7.33	6.03	8.13
	[11.3]	[7.44]	[13.1]
Wage low skilled (thousands)	4.30	3.85	4.68
	[2.33]	[1.92]	[2.57]
Panel C: Commuting Distance			
Km distance to CH border	-	17.0	-
		[19.3]	
Time distance to CH border (min)	-	24.7	-
		[24.5]	
Lives within 30 min to border	-	0.79	-
Lives within 30 km to border	-	0.88	-
Number of spells	5898061	1125973	4772088
Number of workers	419077	146016	273061

Notes: Average characteristics of Italian immigrants working in Switzerland by resident permit. Column (1) includes all Italian workers. Column (2) refers to Cross Border Workers, and column (3) to Resident Immigrants for completeness. Panel A and B display demographics and job characteristics. Panel C shows information about cross borders' commuting on which I leverage for my analysis. Characteristics are averaged across all individuals who have ever worked in Switzerland at the time of their first employment spell. Swiss Social Security data.

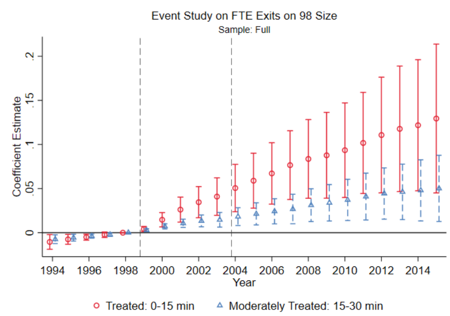
E Robustness exercises

Figure 19: Robustness of Exits

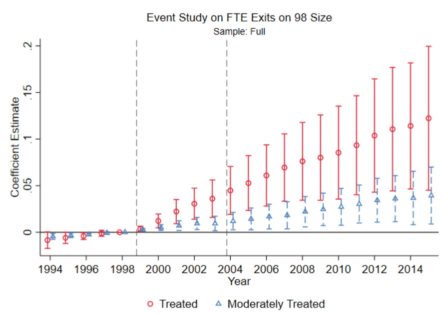
(a) No controls



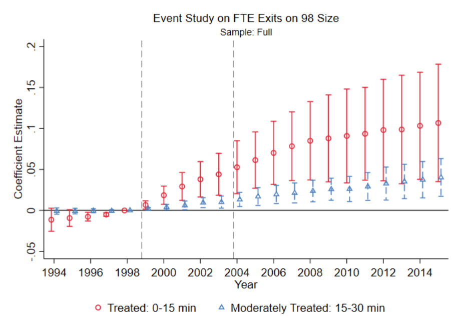
(b) Firm FE



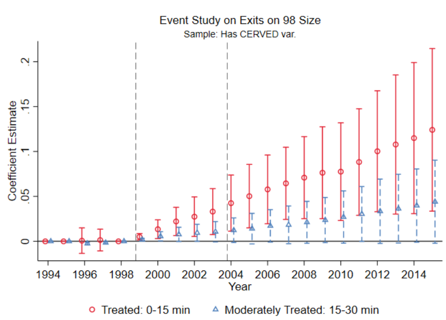
(c) NUTS III & Bartik



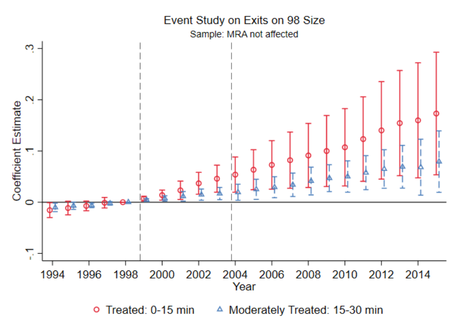
(d) Residence of median worker



(e) Cerved



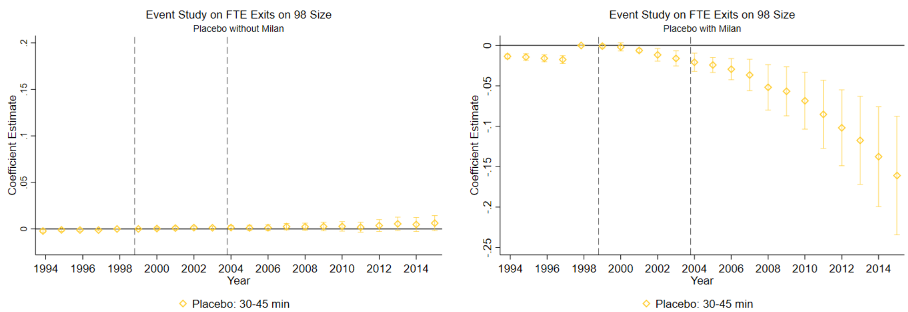
(f) Not MRA Affected



Notes: Figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red circles) and 15-30 min distance bin (blue triangles) of a regression based on equation (2). The dependent variable is cumulated full-time equivalent (FTE) exits over total employment in 1998. Regressions are weighted using the total workforce in 1998 in a cell. Panel (a) includes treatment dummies only. Panel (b) includes firm fixed effects. Panel (c) includes NUTS-III trends and a Bartik control for shifts in employment. Panel (d) locates firms using the residence of the median worker. Panel (e) restricts the sample to firms with balance sheet information. Panel (f) excludes firms affected by reductions in trade costs. Standard errors clustered at the local labor market level. INPS data.

Figure 20: Robustness of Exits: Placebo

(a) Main placebo (b) Including Milan



Notes: Figure plots coefficient and the 95% confidence interval for the placebo treatment 30-45min distance bin (yellow diamonds) of a regression based on equation (2). The dependent variable is cumulated full-time equivalent (FTE) exits over total employment in 1998. Regressions are weighted using the total workforce in 1998 in a cell. Panel (a) excludes firms in Milan as in the main sample. Panel (b) includes firms in Milan. Standard errors clustered at the local labor market level. INPS data.

Table 22: Robustness of Exits

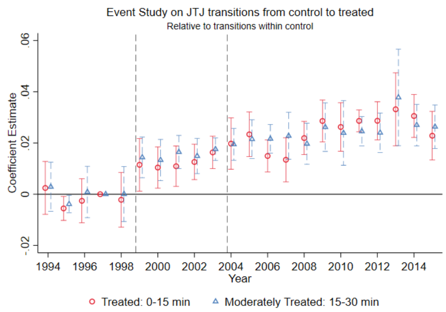
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Strongly Treated					
Transition×($d<15$)	0.020	0.038	0.027	0.023	0.022	0.022	0.025		
	(0.010)*	(0.011)***	(0.0066)***	(0.0061)***	(0.0061)***	(0.0061)***	(0.0065)***		
Free×($d<15$)	0.15	0.10	0.088	0.081	0.081	0.081	0.086		
	(0.029)***	(0.031)***	(0.025)***	(0.023)***	(0.023)***	(0.023)***	(0.024)***		
				Moderately Treated					
Transition×($15<d<30$)	-0.0024	0.016	0.013	0.0084	0.0083	0.0083	0.0091		
	(0.0039)	(0.0044)***	(0.0034)***	(0.0028)***	(0.0027)***	(0.0027)***	(0.0031)***		
Free×($15<d<30$)	0.093	0.039	0.036	0.026	0.026	0.026	0.027		
	(0.014)***	(0.013)***	(0.012)***	(0.0094)**	(0.0093)***	(0.0093)***	(0.010)**		
				Placebo					
Transition×($30<d<45$)								0.00083	0.0036
								(0.0016)	(0.0033)
Free×($30<d<45$)								-0.0028	-0.036
								(0.0062)	(0.012)***
Mean y	0.08	0.08	0.08	0.08	0.08	0.08	0.10	0.09	0.10
Time FE		X	X	X	X	X	X	X	X
Firm FE			X	X	X	X	X	X	X
NUTS III				X	X	X	X	X	X
Bartik					X	X	X	X	X
Controls						X	X	X	X
Milan							X		X
F-stat	73.2	20254.7	4795.7	5.74	4.83	4.83	7.20	3.25	34.1
R2	0.035	0.13	0.66	0.68	0.68	0.68	0.50	0.68	0.50
Obs.	843440	843440	843287	843287	843287	843287	1111270	653199	921182

Clustered Standard Errors at local labor market level (* P<.05, ** P<.01).

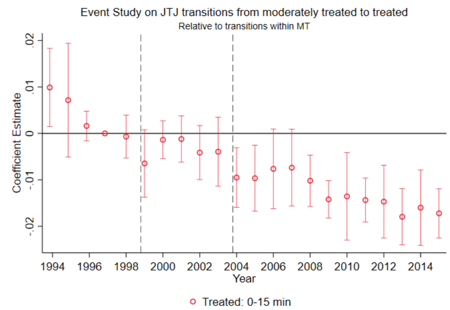
Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of establishment-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in is cumulated full-time equivalent (FTE) exits over total employment in 1998. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data.

Figure 21: Internal mobility of workers: Job to job transitions

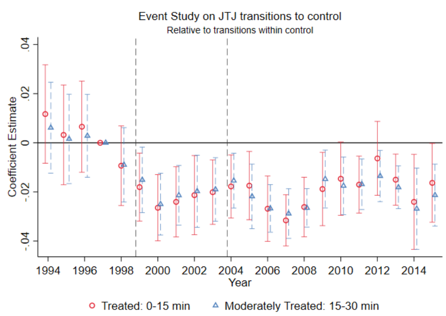
(a) From control to treatments



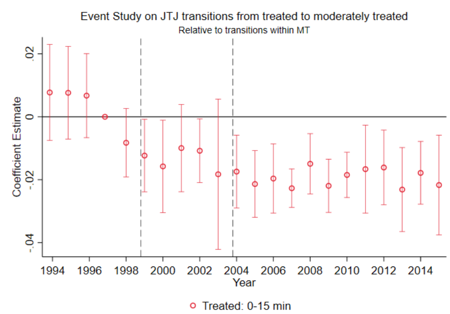
(b) From MT to T



(c) Transitions to control



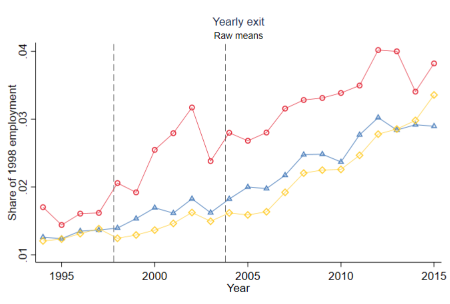
(d) Transitions from T to MT



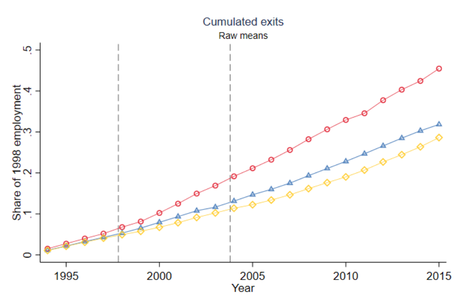
Notes: Figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red circles) and 15-30 min distance bin (blue triangles) of a regression based on equation (2). The dependent variable is job to job transitions. Regressions are weighted using the total workforce in 1998 in a cell. Panel (a) shows transitions from control to moderately and treated firms as share of total transitions in control. Panel (b) shows transitions from moderately to treated firms as share of total transitions in moderately treated firms. Panel (c) shows transitions from treated and moderately treated to control firms as share of total transitions in control. Panel (d) shows transitions from treated to moderately treated firms as share of total transitions in moderately treated. INPS data.

Figure 22: Raw means of yearly and cumulated exits

(a) Yearly



(b) Cumulated



Notes: Figure plots raw means of exits for the 0-15min distance bin (red circles), the 15-30 min distance bin (blue triangles), and control group (yellow diamond).

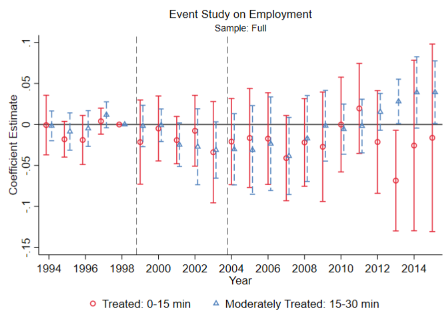
Table 23: Number of hiring, separations, and exits as share of employment in 1998

	(1) Hiring	(2) Separations	(3) Separations resulting in exits
		Panel A: Strongly Treated	
Transition*(d<15)	0.16	0.15	0.025
	(0.065)*	(0.061)*	(0.0065)**
Free*(d<15)	0.48	0.46	0.086
	(0.22)*	(0.20)*	(0.024)**
Relative Effect	0.44	0.48	1.7
		Panel B: Moderately Treated	
Transition*(15<d<30)	0.11	0.12	0.0091
	(0.054)*	(0.058)	(0.0031)**
Free*(15<d<30)	0.35	0.32	0.027
	(0.16)*	(0.15)*	(0.010)**
Relative Effect	0.32	0.34	0.59
Mean of Dep. Var.	**1.08**	**0.96**	**0.056**
Firm FE	X	X	X
Time FE	X	X	X
Nuts III trend	X	X	X
R2	0.62	0.49	0.50
F-stat	11.5	18.2	7.20
Observations	1111270	1111270	1111270

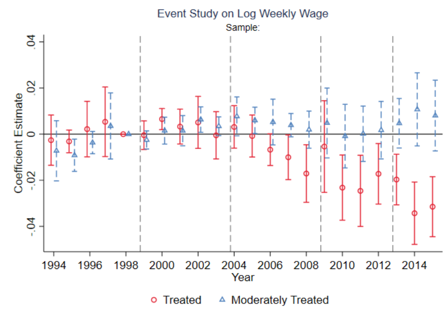
Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of establishment-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable is cumulated full-time equivalent (FTE) hiring in column 1, separations in column 2, and exits in column 3 as share of employment in 1998. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. This sample includes firms in Milan. INPS data.

Figure 23: Robustness: Event study on main outcomes

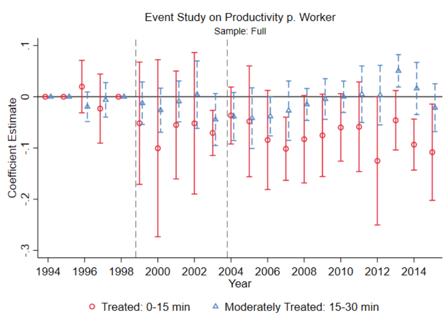
(a) Log size



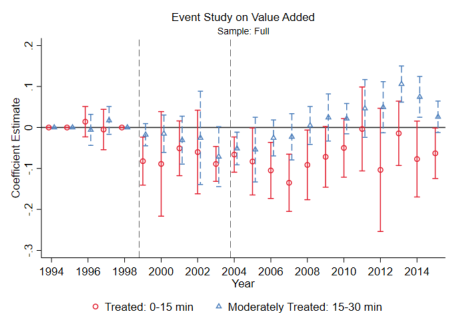
(b) Average log wage



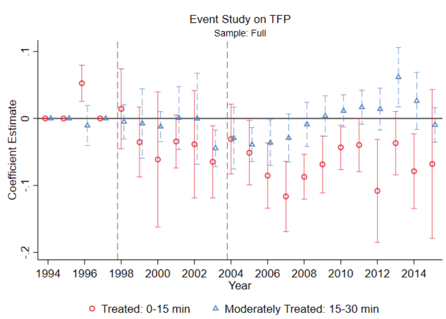
(c) Log value added per capita



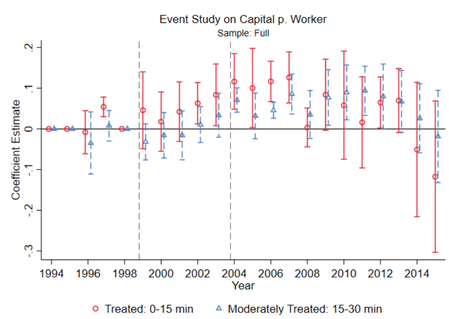
(d) Log value added



(e) TFP



(f) Log assets per capita



Notes: Figure plots coefficient and the 95% confidence interval for the 0-15min distance bin (red circles) and 15-30 min distance bin (blue triangles) of a regression based on equation (2). The dependent variables are the main outcomes reported in table 5. Regressions are weighted using the total workforce in 1998 in a cell. Event studies of panels (c) - (f) start in 1996 when balance sheets data are available. Standard errors clustered at the local labor market level. INPS and *Cerved* data.

Table 24: Margins of adjustment: Cerved firms only

	(1) Log Firm Size	(2) Average Log Wage	(3) Log Value added per capita	(4) Log Value Added	(5) TFP	(6) Log Assets per capita
			Panel A: Strongly Treated			
Transition×($d < 15$)	-0.0049	0.0081	-0.065	-0.069	-0.072	0.055
	(0.016)	(0.0051)	(0.041)	(0.034)	(0.031)*	(0.050)
Free×($d < 15$)	-0.016	-0.013	-0.075	-0.076	-0.095	0.068
	(0.028)	(0.0081)	(0.024)**	(0.033)*	(0.021)**	(0.021)**
			Panel B: Moderately Treated			
Transition×($15 < d < 30$)	-0.033	0.0071	-0.0095	-0.035	-0.0087	0.0066
	(0.020)	(0.0027)*	(0.017)	(0.022)	(0.013)	(0.024)
Free×($15 < d < 30$)	0.0039	0.0065	-0.0077	0.0041	-0.0033	0.069
	(0.013)	(0.0056)	(0.014)	(0.019)	(0.0096)	(0.022)**
Firm FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Nuts III trend	X	X	X	X	X	X
R2	0.88	0.36	0.62	0.86	0.71	0.76
F-stat	6.77	6.19	3.97	2.31	10.2	7.47
Observations	282190	6497661	270497	270497	267493	279970

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table replicates results from Table 5 including only firms with balance sheet information. All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is log FTE employment. The dependent variable in column 2 is average log weekly wages, treatment is defined at the firm level but observations are workers within a firm. The dependent variable in column 3 is log value added per employee. The dependent variable in column 4 is log total value added at the firm. The dependent variable in column 5 is TFP. Total assets are tangible and intangible assets. The dependent variable in column 6 is log total assets per employee. Total assets are tangible and intangible assets. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data and *Cerved* data. Columns 3-4 rely on firms for which balance sheets data are available.

Table 25: Margins of adjustment: Placebo

	(1) Log Firm Size	(2) Average Log Wage	(3) Log Value added per capita	(4) Log Value Added	(5) TFP	(6) Log Assets per capita
			Panel A: Strongly Treated			
placeboTrans	-0.032	-0.0043	0.0080	-0.0068	-0.00014	-0.0043
	(0.016)	(0.0012)**	(0.015)	(0.0071)	(0.0065)	(0.023)
placeboFree	-0.022	-0.0048	-0.013	-0.021	-0.030	0.035
	(0.024)	(0.0023)	(0.018)	(0.023)	(0.017)	(0.015)*
Firm FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Nuts III trend	X	X	X	X	X	X
R2	0.87	0.40	0.60	0.86	0.70	0.75
F-stat	.	.	.	.	.	.
Observations	653199	10584632	220680	220680	218175	228307

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table replicates results from Table 5 including only firms with balance sheet information. All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is log FTE employment. The dependent variable in column 2 is average log weekly wages, treatment is defined at the firm level but observations are workers within a firm. The dependent variable in column 3 is log value added per employee. The dependent variable in column 4 is log total value added at the firm. The dependent variable in column 5 is TFP. Total assets are tangible and intangible assets. The dependent variable in column 6 is log total assets per employee. Total assets are tangible and intangible assets. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data and *Cerved* data. Columns 3-4 rely on firms for which balance sheets data are available.

Table 26: Margins of adjustment: Including Milan

	(1) Log Firm Size	(2) Average Log Wage	(3) Log Value added per capita	(4) Log Value Added	(5) TFP	(6) Log Assets per capita
			Panel A: Strongly Treated			
Transition×($d < 15$)	-0.011	0.0023	-0.065	-0.069	-0.072	0.055
	(0.016)	(0.0040)	(0.041)	(0.034)	(0.031)*	(0.050)
Free×($d < 15$)	-0.015	-0.014	-0.075	-0.076	-0.095	0.068
	(0.034)	(0.0054)*	(0.024)**	(0.033)*	(0.021)**	(0.021)**
			Panel B: Moderately Treated			
Transition×($15 < d < 30$)	-0.016	0.0047	-0.0095	-0.035	-0.0087	0.0066
	(0.013)	(0.0023)*	(0.017)	(0.022)	(0.013)	(0.024)
Free×($15 < d < 30$)	-0.0064	0.0073	-0.0077	0.0041	-0.0033	0.069
	(0.020)	(0.0055)	(0.014)	(0.019)	(0.0096)	(0.022)**
Firm FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Nuts III trend	X	X	X	X	X	X
R2	0.87	0.39	0.61	0.86	0.69	0.75
F-stat	3.39	36.9	3.97	2.31	10.2	7.47
Observations	1111270	19918528	373190	373190	367167	387722

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table replicates results from Table 5 including only firms with balance sheet information. All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is log FTE employment. The dependent variable in column 2 is average log weekly wages, treatment is defined at the firm level but observations are workers within a firm. The dependent variable in column 3 is log value added per employee. The dependent variable in column 4 is log total value added at the firm. The dependent variable in column 5 is TFP. Total assets are tangible and intangible assets. The dependent variable in column 6 is log total assets per employee. Total assets are tangible and intangible assets. Transition is a dummy equal to one between 1999 and 2003, whereas Free is one from year 2004 onward. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. INPS data and *Cerved* data. Columns 3-4 rely on firms for which balance sheets data are available.

Table 27: Summary DID Table: Recruitment of workers

	(1) Post-Reform Control Group	(2) Post-Reform Treatment Group	(3) Post-Reform Difference (2)-(1)
Panel A: Labor force			
Weeks to find key worker	8.51	9.19	0.67
	[6.15]	[5.39]	(2.43)
Location problem in finding key worker	0.13	0.25	0.12
	[0.34]	[0.46]	(0.14)
New worker: adequate	0.77	0.64	-0.13
	[0.43]	[0.51]	(0.18)
Key worker: training days	17.4	4.97	-12.4
	[20.4]	[6.94]	(8.06)
Number of obs	92	16	108
Number of firms	58	9	67

Notes: Variable *Location problem* takes value 1 if firms report its location being an obstacle in recruiting a key worker. Variable *New worker: Adequate* takes value 1 if the firms report the newly hired key worker to be adequately suited for the job. INVIND survey data. INVIND is the annual survey on manufacturing and service firms conducted at the Bank of Italy. Surveyed firms have at least 20 employees. Given the size limit, and the specificity of my treated labor market, very few firms from this survey match with my sample. Evidence produced with this data should be taken as purely suggestive.

Table 28: Summary DID Table: Capital

	(1) Transition Control Group	(2) Transition Treatment Group	(3) Post2004 Control Group	(4) Post2004 Treatment Group
Panel A: Firm Capital				
Share expenses intangible capital	0.52	0.18	0.50	0.38
	[0.47]	[0.36]	[0.46]	[0.46]
Share expenses real estate	0.18	0.48	0.25	0.33
	[0.32]	[0.41]	[0.39]	[0.42]
Share expenses machines	0.22	0.30	0.14	0.11
	[0.35]	[0.32]	[0.31]	[0.28]
Share expenses transportation	0.014	0.018	0.0054	0.0039
	[0.050]	[0.036]	[0.042]	[0.036]
Panel B: Firm Distance				
Driving km from firm to border	49.7	18.5	49.5	18.6
	[10.7]	[8.27]	[10.8]	[8.32]
Driving min from firm to border	48.4	21.9	48.3	22.0
	[8.37]	[6.55]	[8.55]	[6.54]
Number of obs	256	50	671	105
Number of firms	88	15	102	16

Notes: Panel A reports summary statistics on the type of capital in which firms in the INVIND survey invest. Table reports the share on total capital expenditure over: intangible capital, real estate, machines, and transportation means. Residual categories not included int he table are fixed used capital, and leasing capital goods. INVIND is the annual survey on manufacturing and service firms conducted at the Bank of Italy. Surveyed firms have at least 20 employees. Given the size limit, and the specificity of my treated labor market, very few firms from this survey match with my sample. Evidence produced with this data should be taken as purely suggestive.

Table 29: Share of Patents

	(1) Total Patents filed share of 2003 firms	(2) Total Patents published share of 2003 firms	(3) Yearly Patents filed share of 2003 firms	(4) Yearly Patents published share of 2003 firms
		Panel A: Treated		
Free×($d < 15$)	-0.022	-0.013	-0.0018	-0.00083
	(0.030)	(0.030)	(0.0026)	(0.0027)
		Panel B: Moderately Treated		
Free×($15 < d < 30$)	-0.021	-0.015	-0.0013	-0.00098
	(0.036)	(0.038)	(0.0024)	(0.0026)
Mean of Dep. Var.	**0.045**	**0.043**	**0.011**	**0.011**
Firm FE	X	X	X	X
Time FE	X	X	X	X
Nuts III trend	X	X	X	X
R2	0.54	0.52	0.41	0.42
F-stat	0.41	0.11	0.27	0.077
Observations	15444	15444	15444	15444

Notes: Standard errors are clustered by local labor market (* P<.05, ** P<.01). The table presents results of municipality-level DiD regressions following equation (1). All regressions account for establishment fixed effects, period fixed effects, and linear trends per NUTS-III region. The dependent variable in column 1 is share (of 2003 patents) total filed patents over total number of firms in a municipality in 2003. The dependent variable in column 2 is the share of total published patents. The dependent variables in column 3 and 4 are respectively the share of yearly filed and published patents. $I(d_j \leq x)$ and $I(y < d_j \leq z)$ indicate whether a firm is located less than x travel minutes or between y and z travel minutes from the next border crossing, respectively. The regressions are weighted using the average establishment size (in FTE) as weight. Data on patents come from the Infocamere database at the Bank of Italy. As only patenting firms are included in the estimation, results lack of precision. The regression reports the free access phase only, as data are available only from 2000 onward.