Labor Market Competition, Wages and Worker Mobility *

Flavio Hafner [†]

December 8, 2019

JOB MARKET PAPER

Please click here for the most recent version.

Abstract

I study how removing barriers to worker mobility impacts the local labor market. Exploiting a quasi-experiment in which French border commuters gained access to the high-paying Swiss labor market, I show that the market integration leads to improved labor market outcomes among non-movers, and particularly those who are low-skilled. The difference-in-differences research design compares treated French labor markets in the border area to Switzerland with a matched control group of labor markets located in other parts of France. The empirical results show that within the first three years, low-skill wages rise by 1.6 percent and low-skill employment by around 3 percent. The results are consistent with a framework of monopsonistic competition in the labor market where firms have some wage-setting power, especially in the low-skill labor market. In the framework, the labor market integration both increases the outside options of workers and makes the supply to firms more elastic, which raises wages and employment. Enhancing worker mobility may therefore have pro-competitive effects on the labor market that reduce employers' monopsony power and improve the labor market outcomes of workers.

Keywords: wages, job search, monopsony, outside options, commuting
JEL classification: J08, J21, J31, J42, J60, R23

1. Introduction

Worker mobility is important for both the economy and for individual workers. On the aggregate level, worker mobility not only equilibrates labor demand and supply across space, but the reallocation of workers across firms and locations may also fuel productivity growth. On the individual level, the ability to change jobs and place of work insures workers against negative economic shocks and helps them move up the job ladder. Topel and Ward (1992), for instance, show that switching employers can contribute as much as one third to young workers' wage growth. Since theory predicts that the job finding rate affects the labor market equilibrium as a whole (Burdett and Mortensen, 1998), the mere ability to switch jobs may have indirect effects even on workers that ultimately do not move. Given the prevalence of barriers to worker mobility (Davis and Haltiwanger, 2014; U.S. Treasury, 2016; The Economist, 2019; Starr et al., 2019), it is therefore important to understand their effects on the labor market[1].

In the present paper I study how the removal of barriers to cross-border worker mobility affected local labor markets in France. I exploit a policy change in 1998 which made it easier for French residents to find a job in neighboring Switzerland as a cross-border commuter. In particular, Swiss employers no longer had to first look for a suitable worker in Switzerland before hiring a cross-border commuter. Given the substantially higher wages in Switzerland, this market integration not only induced many often high-skilled workers to commute into Switzerland, but also improved the outside options of workers who continued to work in the French border region. Using a difference-in-differences research design and comparing treated border regions with a matched set of control regions in other parts of France, I show that average wages of employees in the French border region rise by around 1.7 percent and overall employment increases by around 3 percent three years after the market integration. The wage effects are primarily driven by low- and mid-skill workers. As wages of high-skill workers do not change, the skill premium among employees in the border region declines. The increase in employment stems mainly from low-skill workers. Even though high-skill employment increases by a similar magnitude, the effect is imprecisely estimated. I also show that before the market integration, wages and employment grow at a similar rate for all skill groups in the treatment and in the control regions. This supports the identification assumption that wages and employment in the treated and the control regions would have evolved on parallel trends in absence of the market integration.

The findings are not driven by other simultaneous policy changes and robust to controlling for more characteristics of the labor markets before the market integration. First, other agreements accompanied the labor market integration and they could have affected the border regions differently from the control regions. Yet, when focusing on a small set of

---

[1]For instance, 30 million American workers are covered by non-compete agreements which prevent them from accepting a job at a competing firm, even though a minority of workers possesses trade secrets. Difficulties in transferring pension rights across occupations in France also make it harder for workers to change their jobs.

tradable industries that were not affected by other agreements, I find similar wage effects, while the employment effects get larger but less precise. Around the same time, France also changed the working hours legislation (Askenazy, 2013; Goux et al., 2014). Controlling for the exposure to this reform, however, does not change the results. In addition, because the matching relies on a small set of covariates, I also show that controlling for various additional non-matched covariates in the regression does not change the results. Further, the market integration could directly impact worker quality if more able people started commuting to Switzerland. Measuring wage growth for the same worker between two consecutive years, I directly control for changes in worker quality. The wage effects are also robust to varying the way treatment regions are matched to the control regions. In particular, when using an reweighting estimator that compares the treated areas to all labor markets in France (Hainmueller, 2012), I find wage effects similar to the baseline specification[2].

Analyzing various subsamples of firms and workers separately, I show that the wage gains are not driven by any particular sector, but instead wages rise in all sectors by a similar magnitude. In contrast, employment increases in the tradable sector while the point estimates are close to zero or negative in other sectors. Wages grow more quickly at highly productive firms and increase at unproductive firms only later. Similarly, wages rise more in large firms than at small firms. The increase in low-skill employment also comes from large firms that start employing more low-skill workers.

Both the average treatment effects as well as the heterogeneity across sectors and firms are consistent with a mechanism where the labor market integration increases workers' outside options and makes the labor market more competitive. In several models of imperfectly competitive labor markets, a workers' wage is a weighted average of her outside option and her marginal product. A perfectly competitive market is the limiting case in which individual firms face a flat inverse labor supply curve. Firms take wages as given and workers earn their marginal product. In contrast, if the market is not perfectly competitive, for instance because of search frictions (Burdett and Mortensen, 1998; Bontemps et al., 2000) or workplace differentiation (Boal et al., 1997; Bhaskar et al., 2002; Card et al., 2018), the inverse supply curve to individual firms is not flat, but slopes upward. In this case, firms' monopsony power in the labor market leads to lower wages and lower employment compared to a perfectly competitive market.

I assess the competitiveness of French labor markets by skill group following Card et al. (2018). In particular, I study how skill-specific wages at the firm are associated with the firm's productivity. In more competitive labor markets, wages are more strongly associated with firm productivity and less strongly associated with workers' outside options. Exploiting productivity shocks to the firm net of industry-wide shocks and controlling for skill-specific sorting to firms, I show that wage growth of incumbent high-skill workers in France is more strongly associated with changes in productivity at the firm than wage

---

[2]I do not use synthetic controls because the three pre-treatment period are insufficient to find appropriate weights.

growth of incumbent low-skill workers[3]. This suggests that the labor market for low-skilled workers is less competitive. Thus the improved outside options from the market integration raise wages of low-skill workers more than wages of high-skill workers. A possible reason for why the labor market for low-skilled workers is less competitive is geographic mobility. I show that less educated workers are less mobile than more educated workers[4]. They commute shorter distances and migrate less within France. This suggests that low-skill workers receive fewer job offers from across France, or have stronger geographic preferences as to where they work than high-skilled workers do. The labor market integration then increases the pool of potential employers, and more so for low-skilled workers whose labor markets are more local. This makes labor supply to individual firms in France more elastic and the labor market becomes more competitive. As a result, employment rises. Wages increase more at more productive firms because they are better able to raise wages than less productive firms[5].

Lastly, the market integration also made it more attractive to live in the French border region because of an option value of getting a high-wage job in Switzerland (Harris and Todaro, 1970). It represents an amenity for working in a firm in the border region. Because high-skill workers are more mobile, they respond most strongly to the improved amenity. Data from the Labor Force Survey suggest that highly educated workers stay longer in the border region, and that is not the case for other education groups. As a result, the supply curve of high-skill workers shifts out again, which overcompensates for the outflow to Switzerland and leaves high-skill wages unchanged.

Several other competing channels cannot explain all the findings. One channel is that the integration increased the demand for local non-tradable services because of the high wages that commuters earn in Switzerland but likey spend back at their place of residence. The channel, however, is not consistent with no employment gains in the non-tradable sector and higher employment in the tradable sector. Second, the reduction in the skill premium could also come from the higher supply of high-skill workers which raises the demand for low-skill workers (Katz and Murphy, 1992). Yet, I find no evidence that the relative supply of high-skill workers increased. Another explanation for higher low-skill wages could be low-skill biased technology. As primarily high-skill workers leave to Switzerland, firms could start adopting technologies that raise the productivity of low-skill workers. Results from estimating production functions suggest, however, that the marginal product of low-skill workers did not change. Finally, a bargaining model could also explain the wage effects (Beaudry et al., 2012) but not the employment effects because firms would create fewer jobs in response to better outside options of workers.

---

[3]Using a different methodology, Friedrich et al. (2019) find similar patterns in the Swedish economy, and Kline et al. (2019) find that patent allowances increase wages more for high-earning incumbent workers in American firms. Card et al. (2015) study heterogeneity of pass-through by gender.

[4]Because of data limitations I cannot study the migration rate by occupation. The commuting patterns within France are similar when classifying skill groups by education and by occupation.

[5]For instance, in a search model as described in Appendix D, more productive firms have more market power because they face less competition from other firms. When the job offer arrival rate increases, more productive firms raise wages more.

The present paper contributes to three strands of the literature. First, it studies labor market policy in imperfectly competitive markets. A leading example are studies on the minimum wage (Card and Krueger, 1995; Neumark and Wascher, 2010). I show that improving worker mobility can have pro-competitive effects on the labor market, in particular for low-skill workers who are less mobile geographically. Naidu et al. (2016) find similar pro-competitive effect of facilitating employer transitions of immigrants. Relative to their paper the present paper studies the aggregate effects on the local labor market. It also highlights skill differences in the degree of labor market competition that are related to geographic mobility. Policy can enhance worker mobility both at the national and at the local level and the present paper suggests it may be a cost-effective way to improve the labor market outcomes of workers that are particularly immobile. On the one hand, labor market regulations such as employer-sponsored health insurance or the transferability of pension rights may hinder worker mobility across firms (Gruber, 2000; Kleiner and Krueger, 2013; The Economist, 2019). Recent evidence also suggests that only a minority of the workers that are covered by non-compete clauses possess trade secrets (U.S. Treasury, 2016; Starr et al., 2019). These restrictions make employers imperfect substitutes for workers and reduce workers' ability to change employers. On the other hand, improving local access to good jobs – for instance through better commuting access – can have similar effects because workers search very locally for jobs (Manning and Petrongolo, 2017). This suggests that commuting access as an additional tool to improve local labor market outcomes in non-competitive labor markets, while existing literature so far has focused on hiring subsidies and finds mixed evidence of their effectiveness (Neumark, 2011; Kline and Moretti, 2014).

Second, the paper analyses empirically how outside options and employer competition affect wages similar to several recent studies. Jäger et al. (2018) find no evidence that higher unemployment benefits increase wages of employed workers, while Caldwell and Harmon (2018) and Caldwell and Danieli (2018) show that better outside options at other firms do. Beaudry et al. (2012, 2014) show that wage growth spills over across industries within locations. Green et al. (2019) show that long-distance commuting raises wages of non-commuters in sending regions. In contrast to existing studies the present paper shows evidence more consistent with labor market monopsony than with bargaining models. The two classes of models make differing predictions on the employment effect of the market integration and on heterogeneous wage effects across employers. Only a monopsony model can explain an increase in employment and faster wage and employment growth at larger and more productive firms.

Third, the paper speaks to the theoretical sources of monopsony power in the labor market, and the evidence is most consistent with models where the supply curve to individual firms is endogenous to the market structure. The most common models can be grouped into three broad categories. First, there are models of job differentiation. In these models individual employers face upward-sloping supply curves because workers have heterogeneous preferences for different employers. In models with random utility

as in Card et al. (2018) and Lamadon et al. (2019), the supply curve is independent of the market structure. Because of the random utility component there will always be some workers that strictly prefer working for one employer, even when adding more employers. Indeed, as Berry and Pakes (2007) discuss in the IO context, this might be a problematic assumption when studying the effects of introducing new products to the market. When workers care only about a limited number of job characteristics, however, supply elasticities are endogenous (Boal et al., 1997; Bhaskar et al., 2002). In such a model, the market integration can be thought of as increasing the number of jobs nearby. If, besides the wage workers for instance only care about how far they have to commute to their work, the integration provides workers with more close substitutes and their supply to French firms becomes more elastic. Second, there are models with on-the-job search where the degree of competition in the market is measured by how easily workers find better jobs (Burdett and Mortensen, 1998; Bontemps et al., 2000). In these models the labor market integration increases the arrival rate of job offers to workers. This makes the labor market more competitive[6]. Third, static models of oligopsony or dominant firms can also explain why the market integration makes the labor market more competitive (Berger et al., 2019)[7]. In these models, larger firms have more wage-setting power. The market integration decreases the market share of large firms and therefore flattens their residual labor supply curves.

The remainder of the paper is organized as follows. Section 2 provides a conceptual framework to guide the empirical analysis. Section 3 describes the institutional setting and the data sources. Section 4 analyzes commuting from France to Switzerland descriptively. Section 5 presents the empirical research design. The results are in Section 6, Section 7 discusses the mechanism, and Section 8 concludes.

2. Conceptual framework

This section describes the framework through which I will study the effects of the market integration. For a wide class of monopsony models, the wage of worker g depends on her outside option b_g and her marginal product at firm j, p_{ig}. The labor supply elasticity to individual firms is denoted ε^g and measures the degree of competition in the labor market. The wage is then

$$w_{jg} = \frac{1}{1+\varepsilon_g} b_g + \frac{\varepsilon_g}{1+\varepsilon_g} p_{jg} \qquad (2.1)$$

In a perfectly competitive market individual firms have no wage-setting power and pay workers their marginal product. The labor supply to individual firms is infinitely elastic, e.g. $\varepsilon_g \to \infty$. In other words, the inverse labor supply curve to individual firms is flat, and lowering the wage even slightly makes all employees move to other firms. If the labor market is imperfectly competitive, we have $0 < \varepsilon_g < \infty$ and some workers will stay at the

---

[6]Hirsch et al. (2019) find similar evidence in Germany.
[7]See Appendix E for an example.

firm even when it lowers the wage.

Two leading models of monopsony are a search model (Burdett and Mortensen, 1998) and a model with job differentiation as in Card et al. (2018). Both models assume that firms pay a unique wage to all its employees – at least within a skill group – and that worker types are perfect substitutes[8]. In the search model, workers are unable to move to better-paying firms because they cannot immediately find open positions at other firms. The market is more competitive when workers find other jobs more easily. To be specific, it gets harder for the firm to retain workers for a low wage because they easily find other employers that pay more. Note that in the search model, each firm pays a different wage[9] but the expected wage is given by equation (2.1). In the model with job differentiation, workers are unwilling to move to better-paying firms because they particularly like working at one firm, stemming from idiosyncratic tastes for each firm. The market is more competitive when workers have weaker preferences for specific employers, eg, when the idiosyncratic taste shocks are less dispersed.

The labor market integration can impact wages through two different channels. First, it raises workers outside option b_i, as the average outside wage in French firms increases because the bureaucratic cost of getting a job in Switzerland disappears. Second, it can make labor supply to firms more elastic. For instance, workers receive more job offers from across the border, which increases the competition in the French labor market. In the taste-based monopsony model in Card et al. (2018) the supply elasticity is fixed by the dispersion of idiosyncratic tastes, and therefore the market integration only works through the better outside option. In other models with job differentiation, however, the market integration can also increase the supply elasticity to individual firms (Boal et al., 1997; Bhaskar et al., 2002). The key distinction is that when workers only care about a finite number of firm characteristics, then filling up the the space of potential employers gives workers more and more close substitutes (Berry and Pakes, 2007). As a result, workers become more indifferent to work at one firm or another. It is an empirical question as to whether the supply curve to individual firms becomes more elastic or not. The direction of the employment effect and the heterogeneity across firm types will be informative about that question. If the supply curve becomes more elastic, employment expands and wages rise more at more productive firms.

3. Background and main data

This section describes how wages are set in France, the policy experiment I analyze and the data I use.

---

[8]The model in Card et al. (2018) can be extended to include imperfect substitutability, see their paper for details.

[9]When firms are homogenous, which firm pays which wage is indeterminate. When firms are heterogeneous, the productivity distribution pins down the firm wage distribution (Burdett and Mortensen, 1998; Bontemps et al., 2000).

3.1. Wage setting in France

Wages are set at three different levels. The government defines a national minimum wage. Bargaining at the industry level between employers and trade unions defines minimum wages at the industry-occupation level[10]. In 1992 these agreements covered around 90% of workers. Since the agreements only define wage floors, individual employers keep considerabl room to pay higher wages. As a result an important fraction of wages are set at the company-level (OECD, 2004, p. 151), either through bargaining with unions or through individualized pay rises. For instance, in 1998 75% of large firms (above 50 employees) granted their workers individualized pay rises (Barrat et al., 2007). Even though the French labor market is less decentralized than the American or British labor market, it is comparable to other European labor markets such as the German or Dutch market. This characterisation is consistent with the wage dispersion documented for instance by Abowd et al. (1999), and Cahuc et al. (2006) find that employer competition is important for French wages.

3.2. The integration of local labor markets

In 1998, Switzerland and the EU announced a set of bilateral agreements to deepen the economic relations between each other. The agreements broadly facilitated factor mobility. Table B.1 provides a detailed list of all agreements, the primary changes and, if known, their effects. The free movement of people gave citizens the freedom to seek work and settle in the parties' labor markets. Because the EU allows cross-border commuting across its internal borders, local labor markets along the Swiss border became integrated. Before 1998 bureaucratic barriers prevented workers from free border commuting. Only residents from so-called "border municipalities" – defined in a contract in 1948 – were eligible to commute. The general rules were symmetric for French and Swiss commuters. Commuters had to return to their residence every day, their work permits were valid for one year, and changing work location or profession needed to be authorised. Countries specified individually how they issued work permits (Swiss Federation, 1986). Swiss firms could only hire a worker from across the border when they could not find a suitable worker in Switzerland before (Beerli et al., 2018). The integration removed these hiring restrictions, but workers still need to formally obtain a permit. The permit duration increased to five years. Weekly instead of daily commuting became possible (Bundesrat, 1999). During the complete sample period, however, eligibility remained restricted to residents of the border municipalities which will serve as a base for the treatment assignment described in Section 5.

The institutional setting makes it unlikely that the integration of local labor markets were a result of special interests in the French-Swiss border region. It was Switzerland that asked for negotiations in the mid-1990s during which the EU's position was defined by general principles. On several occasions the European Commission stated that the

---

[10]The majority of these agreements is at the national level.

agreements had to comply with existing European norms (European Commission, 1995; van den Broek, 1996; Bundesrat, 1999), and the integration of local labor markets was merely a consequence of that more general rule. While the agreements became officially active in 2002, Swiss authorities already started relaxing the restrictions on commuting in 1999 (Beerli et al., 2018). I will thus use 1998 as the base year for the empirical analysis.

3.3. Data sources

3.3.1. Full-count worker records

The analysis uses a matched employer-employee dataset from France provided by the Statistical Office (INSEE). The data contain annual social security declarations filed by employers excluding the self-employed. I use the vintage called *DADS postes* (DADS = "Déclarations annuelles des données sociales"). The data report employment spells between individuals and establishments[11]. Data on spells report total salary, total hours worked, gender, age, occupational category, municipality of work and residence, the start and end date, as well as an indicator whether it is the individual's main spell in that year[12]. If the worker was employed at the same firm in the previous year, information on wages and hours from that year are also available. If the workers was employed at another firm in the previous year, the information on the preceding spell is not available, however. I focus on the main employment spell of each worker and keep those that are full-time employed as of June 30 in each year. I keep workers that are between 15 and 64 years old. I drop apprentices, interns and workers in the agricultural sector. I also drop workers with missing data on occupation or place of work.

Employees in any year are either firm stayers or new hires. Firm stayers are workers that work at the same employer in two consecutive years. The remaining workers are new hires. I focus on firm stayers because I can calculate changes in outcomes at the individual level. It controls for unobserved individual heterogeneity, but does not allow me to study in detail how the effects on wages of newly hired workers. I build a dataset of wage growth and employment at the skill × year × labor market cell. I classify workers into skill groups based on their two-digit occupational classification[13] similar to Combes et al. (2012) and Cahuc et al. (2006)[14]. High-skill occupations are managers, executives, scientists, engineers, lawyers. Mid-skill occupations are technicians, foremen, skilled blue collar workers and administrative employees. Low-skill occupations are unskilled blue and white collar workers (craft, manufacturing, sales clerks). It will also be important to distinguish different types of industries which I group as follows. Tradable industries are all manufacturing sectors and business services as in Combes et al. (2012). Construction and

---

[11]Eg, if an individual is employed at two different establishments, there are two spells.

[12]The definition is provided by INSEE and based on the spell's duration and total compensation.

[13]There was a major revision of occupational classifications in 2002, but the 2-digit variable used for the skill assignment ("socioprofessional category") is reported with almost no change until 2008. It changes in 2002 for some managers, but both their old and their new two-digit socioprofessional category lie in the high-skill group.

[14]I pool skill groups 2 and 3 from Cahuc et al. (2006).

non-tradable industries are defined as in Mian and Sufi (2014). The remaining industries are classified as other. Local labor markets are defined by INSEE. There are 297 units in France and their size and commuting patterns are comparable to counties in the United States. To measure aggregate growth of hourly wages, I first residualize wages with respect to gender, age and year where I winsorize wages at the first and 99th quantiles. Individual wage growth is then the change in the log hourly wage between two consecutive years. I aggregate the individual wage growth at the cell level[15]. The main outcome of interest is then the cumulative wage growth since 1998. For instance, the outcome in 2002 will be the sum of the wage growth for the years 1999 to 2002.

3.3.2. Balance sheets from tax records

I combine these data with firm-level balance sheet data drawn from the *FICUS*. The data contain annual information on the total wage bill, the book value of capital, sales, material use as well as other observables such as the municipality of the headquarters, a unique firm identifier and the five-digit industry of economic activity (NACE classification). The data are quasi-exhaustive and exclude very small firms with annual sales of less than 80'300 Euros[16] as well as finance and insurance companies. The data cleaning and preparation follows Gopinath et al. (2017), and norminal variables are deflated at the two-digit industry level with deflators from EU-KLEMS. On the one hand I use the data at the firm level to estimate production functions and rent-sharing regressions. On the other hand I calculate separate outcomes at the labor market × year level where I aggregate the firm-level variables. I distinguish between single- and multi-establishment firms because the data are only available at the the level of the taxable unit.

4. Descriptive analysis

I now describe the labor markets along the border in 1998 and show how French workers reacted to the new employment opportunities. I do this for three education groups separately: compulsory education or less, secondary education, and tertiary education. In the main analysis I group workers by skill based on occupation. I use education here because I can better compare wages across the border. Since the occupation is not defined for non-employed workers, it also enables me to assess transitions between labor market statuses.

In the first part I use data from the Swiss Employment Structure Survey (Bundesamt für Statistik, 2017) and from the 4% worker panel in France which both report the education of the workers[17]. In the second part I use the French Labor Force Survey from 1994 to 2002, a rotating panel survey of the French population. The survey samples individuals at the place of residence in March of three consecutive years. In each interview they report

---

[15]Because individual growth rates exhibit large tails I winsorize them at the first and 99th percentile.

[16]This threshold is from 2010, but only changes marginally over time (Di Giovanni et al., 2014).

[17]I harmonize education groups according to the ISCED-1997 classification.

their labor market status for each of the 12 preceding months. I identify cross-border commuters by their country of work.

4.1. French workers could gain from commuting to Switzerland

Figure 1 depicts large wage differences between France and Switzerland in 1998. The Figure plots the average nominal log wage in Euros for three education groups in the Swiss and the French parts of the border region. French wages are in red and Swiss wages are in green. Wages for highly educated workers were around 3 log points in Switzerland and a bit more than 2 log points in France, implying that average wages for high-skill workers were more than twice as high in Switzerland than they were in France. The wage differences for less-educated workers were smaller. For workers with mandatory education, the Swiss wages were still around 80 percent higher than French wages.

Appendix A.1 graphically documents other dimensions of the labor markets along the border. French labor markets are less dense than their Swiss neighbors. Wages do change discontinuously at the border for all education groups, supporting the conclusion drawn from comparing average wages in the two countries. French labor markets are between 13 and 96 minutes away from the next border crossing to Switzerland[18].

4.2. Employees in high-skill professions reacted most strongly

For treated and control areas, Figure 2a shows the share of the labor force that commutes to Switzerland for 1993 to 2002. There are no border commuters from the control area. In the treatment area the share of commuters to Switzerland decreases from above 4% in 1993 to below 4% in 1998. The trend reverses after 1999[19] and in 2002 almost 6% of the labor force commutes to Switzerland[20]. Figure 2b plots the same number for the three education groups in 1998 and 2002. The red bars refer to 1999, the green bars to 2002. Workers of all type start commuting more, suggesting that the market integration raised employment opportunities for all workers. There is, however, a strong education gradient. Many new commuters are highly educated; the share of cross-border commuters of the high-skill labor force increases from below five percent to more than eight percent in 2002. These patterns confirm the findings by Beerli et al. (2018) who study the composition of new commuters in Switzerland after the market integration.

To understand better which workers responded to the newly availabe jobs, I study the transitions of workers from France to Switzerland. In the Labor Force Survey I identify new cross-border commuters that worked in Switzerland in year t but worked in France in year $t-1$. Figure 3 shows that the new commuters were primarily workers that lived

---

[18]Data on the location of border crossings have been thankfully provided by Henneberger and Ziegler (2011).

[19]It is plausible that the trend only reverses after 1999 because the survey is collected in March 1999 and the market integration was only announced in December 1998.

[20]Swiss commuters in France are less well documented. In 2000 0.03% of the Swiss labor force in the border region worked in France (Bundesamt für Statistik, 2000).

and worked in the border area in the previous year. Figures 3a and 3b consider education groups (columns) and years (rows) separately. Figure 3a shows that roughly 75 percent of new border commuters already lived in the border area in the year before they accepted a job in Switzerland. This holds across all education groups and across most years. An exception is the year 2000 when almost 50 percent of new border commuters with a tertiary education did not live in the border area before they accepted a job in Switzerland. Figure 3b zooms further into the group of new border commuters that already lived in the border area in the previous year. It presents transition rates out of employment, unemployment and inactivity to Switzerland, again for the three education groups and each year separately[21]. The majority of those new border commuters did have a job in the border area in the previous year. In each year between four and eight percent of highly educated employees accepted a new job in Switzerland. The number decreases by education as around 2.5 percent of workers with mandatory education accepted a new job in Switzerland. In contrast Swiss firms did not hire any French commuters from inactivity and very few from unemployment.

To bridge the current section to the main empirical part, I present some more evidence by occupation. For four groups of occupation, I calculate average transition rates from 1999 to 2002. The sample contains new commuters that leave their jobs in the French border area to work in Switzerland. Figure 4a shows that the highest outflow was from high-skill occupations such as mangers and engineers. Almost seven percent of those workers left their jobs in France to work in Switzerland. The number is smaller for less skill-intensive professions. Four percent of office employees and a bit more than two percent of manufacturing employees transitioned to Switzerland. The data further suggest that new commuters were positively selected on occupation in each education group. I compare new commuters with stayers in their old job, eg in the year before the new commuters leave to Switzerland. Figure 4b plots the distribution of workers across occupations within education groups both for stayers and for new commuters. 60 percent of new commuters with tertiary education worked in managerial or engineering professions before they accepted a job from Switzerland compared to less than 40 percent of workers with the same education that did not start commuting. Similarly, for workers with secondary and mandatory education, new commuters tend to be drawn from more skill-intensive occupations than stayers, although the patterns are less stark.

To conclude the descriptive analysis, the evidence shows that all French workers could potentially benefit from working in Switzerland. While workers of all education groups took accepted more jobs in Switzerland after the market integration, most of new commuters were highly educated. They lived and worked in the border area before starting a new job in Switzerland. The largest outflow was from managerial and engineering professions.

---

[21]If a worker is employed in France in the previous year and employed in Switzerland in the current year, but has an intermittent unemployment spell bin between, she is classified as a transition from unemployment.

5. Empirical design

5.1. Estimating the effect of the labor market integration

To estimate the effect of the labor market integration, I define labor markets that are at most a distance $\bar{d}$ away from the French-Swiss border as potentially affected by the market integration and thus in the treatment group. This includes, on the one hand, eligible labor markets that contain at least one municipalitiy that is eligible to send commuters to Switzerland as defined in the agreement. On the other hand it also includes areas that are potentially affected through ripple effects across labor markets. Research has shown that commuting linkages across spatial units can create spillovers (Manning and Petrongolo, 2017; Monte et al., 2018; Nimczik, 2018). A shock in one area can impact areas close by, for instance because workers search for jobs close to where they live. It is therefore important to take such spillovers into consideration when estimating the effect of local shocks and policies. Another implication is that spillovers can also impact the control group if it lies close to the treatment area.

I define $\bar{d} = 84$ as the width of a belt drawn around the French-Swiss border that contains the complete area of all eligible labor markets. The treated labor markets are then all 22 labor markets that lie within that belt. Figure 5a shows the set of treated labor markets. The area with eligible municipalities as defined in the treaty is in navy blue, the eligible labor markets are in red, and the labor markets affected by spillovers are in green. The treated labor markets lie within a 96-minutes car drive from the next French-Swiss border crossing. The median commute in France in 2004 was 12 minutes. The treated labor markets therefore lie within ten times the median commute which is how far Manning and Petrongolo (2017) estimate the ripple effects go.

The simplest model compares how outcome y in labor market i for skill group g changes from 1998 to year τ in treatment and control areas in a difference-in-difference manner:

$$\Delta y_{i\tau}^g = \alpha_\tau^g + \beta_\tau^g treat_i + v_{i\tau}^g, \ \forall \tau \neq 1998 \tag{5.1}$$

with

$$\Delta y_{i\tau}^g = y_{i\tau}^g - y_{i1998}^g$$

First differences absorb time-constant heterogeneity at the level of the labor market $\times$ skill group level. α_τ^g accounts for a skill-specific time trend that is constant across all labor markets. The coefficients of interest are β_τ^g which estimate the effect of the labor market integration on workers with skill g for different years. v_{it}^g is an error term orthogonal to the treatment assignment and possibly correlated across space. The hypothesis that $\beta_\tau^g = 0$ for $\tau < 1998$ allows me to test for pre-existing trends between the treatment and control areas before the labor market integration. Failing to reject this hypothesis will support the identification assumption of parallel trends in absence of the labor market integration.

To account for spatial correlation of the error term, I cluster the standard errors at

the level of the departement which is a subnational administrative unit[22]. There are 27 clusters in the matched sample and I use the small-sample correction provided by Imbens and Kolesar (2016). They show that the approach has good coverage rates even in small samples with heterogeneous cluster sizes, and it is easy to compute. For robustness I also estimate bootstrapped p-values using the wild cluster bootstrap (Cameron et al., 2008).

5.2. Matching to find a suitable control group

Equation (5.1) compares the evolution of outcomes in affected areas with non-affected ones. Because the labor market integration was not randomly assigned across labor markets, differences between the treatment and control group may bias the estimated effect. One reason are differing labor market dynamics as wages in the control area could be growing slower than wages in the treatment area already before 1998. Another reason is that labor markets may have different sectorial structures which could therefore be exposed to different time-varying shocks. In both cases the regression in equation (5.1) would wrongly attribute differences in outcomes to the labor market integration when in reality they are driven by other factors.

It is therefore important to find control areas that are as similar as possible to the treated areas. To minimize the risk that spillovers across areas contaminate the control group, I only consider as potential controls labor markets that are at least 150 kilometers away from the Swiss border.

To find suitable control units I use Mahalanobis matching, which minimizes the normalized Euclidean distance between variables across the treated and control groups. It is relatively robust in different settings, in particular in small samples, but the set of included variable should not be too large (Zhao, 2004; Stuart, 2010). I therefore include a limited set of variables that I believe are related to the outcome[23]. I match on the cumulative growth rates of residual wages of firm stayers for the three skill groups between 1995 and 1998 to account for different labor market dynamics before the labor market integration. I match on the following covariates in the cross-section in 1998 to account for other unobserved heterogeneity that could affect wage growth after 1998: employment shares of four sectors (tradable, non-tradable, construction, other), and employment shares of three skill groups. Accounting for differences in the industry structure is important because industries may react differently to the market integration. For instance, the competition for labor increases, firms that sell to a local consumer base may be better able to raise prices and pay their workers more (Harasztosi and Lindner, 2019). Accounting for the distribution of employment across skill groups is important because different I also match on the share of residents that live and work in the same labor market to account for heterogeneous labor supply elasticities which can affect how the labor market integration

---

[22]When a labor market lies in more than one state, I assign it the state where it has the largest employment share in 1998.

[23]I have also experimented with adding more variables but the overall match quality worsens. When matching on fewer variables the effects are similar but the pre-trends are not well matched for some outcomes.

affects the local economies (Monte et al., 2018). I call it the own-commuting share. I loosely refer to the full set of variables as covariates even though some of them are pre-existing trends in outcomes.

I assess balance in the covariates following Imbens and Rubin (2015, Ch. 14). I measure how well their distributions in the treatment group overlap with the one in the control group. I consider three measures[24]. Normalized differences between treatment and control measure the position of the distributions, relative to the population standard deviation. Log ratios of standard deviations between treatment and control measure the dispersion of the distributions. The fraction of treated (control) units that lies in the tails of the values of the control (treatment) units measures how well treatment and control areas overlap in the tails. To be specific, it shows the probability mass of the distribution for the treated units that is outside the 0.025 and 0.975 quantiles of the distribution for the control units, and vice versa. Intuitively it is more difficult to impute the counterfactual for those units because there are not many in the control (treatment) group. For reference, in a randomized experiment this number should be 0.05 in expectation, meaning that 5% of units have covariate values that make imputing missing potential outcomes difficult (see Imbens and Rubin (2015) for more details).

Figure 6 presents normalized differences and log ratios of standard deviations for the variables used for matching. The x-axis denotes the value of the measure and the y-axis denotes the variables. I compare the treated units to the set of controls before and after matching. The red dots use all potential controls, and the green diamonds use only the matched controls. The left panel shows the normalized differences and the right panel the log ratio of standard deviations. For each covariate, the normalized difference with all potential controls and with the matched controls is normalized with respect to the same standard deviation, i.e., the population standard deviation in the treatment and potential control groups. The red dots indicate that there is considerable imbalance in the overall sample. Treated areas have more employment in the tradable sector and a higher own commuting share. Wages grow less in the treatment group than in the pool of potential controls before the market integration. Some covariates are also substantially less dispersed in the treatment group than in the potential control areas, most notably the share of high-skill workers, the wage growth and the own-commuting share. This suggests that treated labor markets are more homogenous than the potential control areas. The green dots indicate that the matching strategy improves balance for most covariates. Normalized differences shrink in all but two cases. The variability of covaraites also shrinks considerably, implying that covariates are more similarly distributed in both the treated and the control areas.

Table 1 presents more detailed numbers for the sample before and after matching. For each variable Panel A compares the treated units to all potential control units, and Panel B compares them to the matched control units. The first four columns show the means and standard deviations of the variables by treatment status. The last four columns show the

---

[24]Imbens and Rubin (2015) use them instead of t-statistics because they are invariant to sample size.

different overlap measures. Columns (5) and (6) contain the same information as Figure 6, and columns (7) and (8) show the overlap measures in the tail of the distributions. The second-last row in each panel measures the overall distance between the covariates of the treated and control units. It is the variance-weighted distance between covariate means of treated and controls. The matching reduces the distance from 1.19 to 0.22. I am not aware of benchmarks for these measures, so I refer to those reported in Imbens and Rubin (2015). They refer to substantial imbalance for a sample with overall distance of 1.78, and to excellent balance for a sample with overall distance of 0.44. These numbers suggest that the matching strategy reaches a reasonable balance between the treated and the control units, which is perhaps not surprising since the potential control areas include both the metropolitan areas of Paris and more rural parts of France. As the covariates are less dispersed in the treated than in the control group, a substantial fraction of control units lies outside the tails of the distribution of the treated units before matching (Panel A, column (7)). The matching brings the tails of the control units closer to the treated units (Panel B, column (7)).

As an alternative matching strategy I also use Entropy Balancing (Hainmueller, 2012)[25]. It finds weights for all potential control units such that the weighted covariate means of the control coincides with the equi-weighted covariate means of the treated units. I then estimate equation (5.1) on all labor markets and weight observations by the entropy weights.

5.3. Identifying assumptions

Input or output markets could transmit the local shock to the rest of the French economy. By comparing labor markets close to the Swiss border with units located elsewhere in France, I assume that the matched control areas are not affected by the labor market integration.

The market reforms which accompanied the labor market integration could affect the French border regions in other ways than through the labor market if their effects were more or less concentrated at the border than in other parts of France[26]. Table B.1 shows the content of the agreements and associated changes in column (2). I give here a short overview of these agreements[27]. An agreement on product certifications reduced the fixed cost of trade in some manufacturing sectors. Evidence from Switzerland shows that the agreement had the strongest effects on imports (Hälg, 2015), suggesting that French firms in the border region could have benefitted from more sales opportunities. An agreement on transport reduced the cost of freight crossing Switzerland by motortrucks by 8.3%. This could have increased profit margins of transportation firms. An agreement on air

---

[25] I do not use synthetic controls because the three pre-treatment period are insufficient to find appropriate weights

[26] Tariffs between Switzerland and the EU had been abandoned already in 1972.

[27] I drop the agreements on agriculture because this sector is dropped from the analysis. I also drop the agreement on research cooperation for which it seems unlikely to have had a direct effect on the economy.

transport possibly made it cheaper to fly. An agreement on public procurement made it easier for French firms to sell to Swiss municipalities[28]. I argue that it is unlikely that the agreements other than the labor market integration had any differential effect on French border region. Transporting people is much more costly than transporting goods (Monte et al., 2018) suggesting that the effect of the labor market integration decays much more quickly across space than the (possible) effects of the other agreements. Consistent with this claim, I find very similar effects when focusing on a small set of tradable industries which were not affected by the trade reform.

The identifying assumption is also violated when labor markets were differentially exposed nation-wide policies around 1998 because they can affect labor market outcomes. One possibility is that the French government substantially increases the legal minimum wage. This could violate the identifying assumption when French-Swiss border regions employ more workers at the minimum wage than the control regions. Similarly, the French government announced a reform to reduce the hours worked per week from 39 hours to 35 hours (Askenazy, 2013). Firms with 20 employees or more had to comply by the year 2000, and early compliers received tax cuts. The law wanted to increase the hourly wages of workers by lowering hours worked per week but keeping monthly wages constant. In robustness checks I control for the regions' exposure to that reform and the results remain unaffected.

6. Results

6.1. Effect on wage growth and employment

Figure 7 presents the main effect of the labor market integration on wage growth of firm stayers. For instance, the effect in 2000 is the sum of wage growth from 1998 to 1999 and from 1999 to 2000. Figure 9 shows the effect of the market integration on log employment. The error bars are 95 percent confidence intervals using standard errors corrected for clustering at the département level. Table 2 contains detailed results on wages and employment for the short- and medium run. I define the short-run effect as the effect in year 1999 and the medium run effect as the effect in year 2001. For inference, the Table shows the standard errors using the Imbens and Kolesar (2016) correction in parentheses, and wild-cluster bootstrapped standard errors (Cameron et al., 2008) in brackets. Significance levels using the two methods closely align with each other.

Panel 7a shows the average effect across all skill groups. The regressions from 1995 to 1997 do not indicate any pre-existing differential trend in wage growth in the treatment group. This is by construction as I match on these trends. Wages start increasing in 1999 and by 2001 they have grown 1.7% more in the treatment region. The effect remains on the level until 2003 and is statistically significant, but the standard errors grow over time.

---

[28]French municipalities and Swiss districts and cantons had already been bound to do so by a WTO agreement since 1996.

Panels 7b to 7d show the estimated treatment effects by skill group. All cases suggest that treatment and control groups are on parallel trends before 1998. Wages of mid-skill workers grow more in the treatment than in the control area from 1995 to 1996 but not significantly so. There is no effect on wages of high-skill workers, and the point estimate turns negative towards the end of the sample period. In contrast wages of mid- and low-skill workers grow significantly after 1998. The point estimates are similar for both groups and range between 1.7 percent for low-skill workers and 2.1 percent for mid-skill workers, but they are statistically indistinguishable from each other.

Turning to the employment effects, Panel 9a shows that overall employment increases by 1.4 percent in the short-run, and by 2.8 percent in the medium run. The effect is, however, imprecisely estimated. The remaining panels show that it is low-skill employment that increases significantly in the short-run but again becomes imprecise after the year 2000, while the magnitude of the point estimate remains throughout the sample period.

6.2. Wage and employment effects across industries

To understand the employment and wage effects documented above, I now study the wage and employment effects across industries. An possible explanation for the positive effects on low-skill workers is that the earnings of new commuters to Switzerland raise the demand for local non-tradable services such as restaurants. I define the non-tradable sector following Mian and Sufi (2014) which are local non-tradable services. The tradable sector is defined as in Combes et al. (2012) and contains manufacturing as well as business services such as law firms. The remaining sectors are split into construction and "other" of which wholesale trade is an important part.

Figure 10 presents wage and Figure 11 the employment effects by industry for the years 1999 and 2001. Table 3 provides all point estimates for wages and employment for the year 2001. Columns 1 and 6 contain the baseline average effects when pooling all workers, and the remaining columns present the results by different industries. Wages grow in all industries. In 2001, the point estimate in the tradable and non-tradable sector is 0.015 (se 0.007 and 0.009 respectively) and very close to the baseline estimate of 0.017. In construction, wages raise substantially more by 0.043 (se 0.016), while it is smaller and not significant in other sectors. Looking at different skill groups gives a very similar picture. Low-skill wages rise by a similar magnitude in the tradable sector as in the baseline, and they are also larger in the construction sector. As Figure 10 shows, the wage effects in 1999 exhibit a similar pattern but are smaller and not precisely estimated. In contrast to the wage effects, the employment effects are concentrated in the tradable sector where, by 2001, overall employment run increases by 4.8 percent while the overall effect is 2.8 percent. In contrast, employment effects in other industries are smaller, not distinguishable from zero and negative for construction. High- and low-skill employment also rises in tradable industries, but the point estimate in the medium run is more imprecise. Figure 11 shows that high- and low-skill employment rise in the tradable sector but not in other sectors

17

also in 1999.

6.3. Robustness

To explore the robustness of the main results I conduct several additional exercises. Table 4 and Figure 8 present the results for the short- and medium-run wage effects, and Table 5 presents the results for employment effects in the same years.

To control for the exposure to national minimum wage changes and to the workweek reduction, I include two additional controls in the regressions. In particular, I control for the share of workers at the minimum wage in 1998. If the government increases the legal minimum wage, these workers would be the most affected by the chane. to control for the exposure to the change in workweek legislation I include the share of employees in large firms in 1998 in the regressions. This is a valid control for exposure to the workweek reduction if large firms did react more quickly to the reform than small firms. Table 4 shows that the wage effects are very similar when controlling for these two policies (column 6) as in the baseline (column 5) for all skill groups. The employment effects are also robust to including these controls (Table 5, column 1 and 2). In the remaining columns of Tables 4 and 5 I control for average wages in 1998 in the area. I do this because I do not directly match on this variable and treatment and control areas differ in their average wages, even after matching. In columns 3 and 7 I control for the average residual log hourly wage. The estimated medium-run average wage effect drops from 0.017 to 0.012 but remains statistically significant at the 10 percent confidence level. It also drops for the medium and low-skill workers but remains significant conventional levels. The employment effects, if anything, slightly increase when controlling for average wages at baseline and remains significant. In columns 4 and 8 I control for skill-specific residual log hourly wages in the labor market, and the estimated wage and employment effects are close to the baseline effects.

Figure 8 shows the estimated medium-run wage effects on low- and mid-skill occupations when including some more controls. The controls are skill shares at baseline, the employment share of different firm size groups, and financial variables such as capital and value added per worker. Including these controls does not alter the estimated effects of the market integration. As pointed out by Oster (2019), coefficient movements should be assessed together with movements in the variation explained by additional controls. The boxes on the right-hand side of the panels in Figure 8 contain the calculated amount of unobservable selection necessary to drive the estimated effect of the market integration to zero, assuming unobservables explain an additional 30 percent of the variation in the outcome than the regression with the controls. In all cases, this statistic lies above 1, implying that the amount of unobservable selection would be stronger than the amount of observable selection in order to make the wage effects disappear.

Other agreements accompanied the labor market integration. A trade reform reduced the fixed cost of trade in some manufacturing sectors by 0.5 to 1 percent of the annual

product value, and it has been documented that the reform increased imports of affected goods to Switzerland (Hälg, 2015). To assess whether this increased trade can explain the positive wage and employment effects in the tradable sector, I compare the estimated wage and employment effects on French border regions in tradable industries that were not affected by the trade reform with the baseline effects and the effects in the tradable industries as a whole. The results for the year 2001 are in Table 6. Columns 1 and 4 present the baseline estimates for wages and employment, respectively, columns 2 and 5 the effect on tradable industries as a whole, and columns 3 and 6 on tradable industries not affected by the trade reform. Column 3 shows that the wage effects both for mid- and low-skill workers are very similar to the baseline effects and even a bit larger than the effect on tradable industries as a whole, and they remain statistically significant. Similarly, in column 6 we see that if anything, employment grew even more in the industries unaffected by the trade reform compared to the overall effects, even though the effects are imprecisely estimated. The evidence suggests that the positive employment and wage effects cannot be explained by a simultaneous reduction in trade cost.

To further assess the robustness of the findings, I use an alternative matching strategy. In particular, I use a entropy balancing following (Hainmueller, 2012). It is a reweighting estimator which creates weights across all potential control units so as to perfectly balance the first and second moment of the covariate distribution. I use the weights as regression weights in equation (5.1). Appendix C.1.2 provides further details on the matching approach. Figure A3 shows the estimated effects for the baseline sample with a solid line and points and for the entropy balanced sample with a dashed line and diamonds. In general the magnitude and the precision of the wage effects are similar when using either of the two approaches. For low-skill workers, there is an insignificant pre-existing positive trend in wage grwoth, and the estimated effect of the market integration on low-skill wages is less precise than the effect with the baseline matching strategy. The employment effects, however, differ more between the two samples. First, entropy balancing does not find a positive employment effect overall. Second, while it finds a positive effect on low-skill employment of a similar magnitude and precision as the baseline matching strategy does in the year 1999, the estimated effects declines afterwards and even becomes negative. As discussed in Appendix C.1.2, this is likely because entropy balancing fails to pick up some unobserved heterogeneity which is responsible for the differing employment effects, while the baseline matching strategy does capture it.

7. Interpretation

The preceding analysis shows that the labor market integration increased both wages and employment, in particular for low-skill workers. Together with the effect heterogeneity across employer types, it suggests that the market integration not only raised workers' outside option but also made their supply to French firms more elastic. The better outside options should raise wages more in less competitive markets. The next section studies the

competitiveness of French labor markets and the role of geographic mobility in order to understand the effects of the labor market integration. It then discusses alternative explanations which cannot explain all the findings.

7.1. Worker mobility and labor market competition

First I assess the pass-through of productivity growth to incumbent wages in the French labor market, following Card et al. (2018). The idea is based on equation (2.1) where workers with a higher supply elasticity earn a larger share of the marginal product. Thus, changes in firm productivity affect wages of workers with a higher supply elasticity more strongly[29]. Among French single-establishment firms from 1995 to 2003, I estimate the following regressions for each skill group g separately:

$$\Delta w_{gijt} = \beta_g \Delta p_{ijt} + \gamma_{gi} + \gamma_{gjt} + u_{gijt} \tag{7.1}$$

where i identifies the firm and j the four-digit industry of the firm. w_{gijt} is the wage growth of incumbent workers between year $t-1$ and t that stay at the firm, Δp_{ijt} is the change in log value added per worker between $t-1$ and t, and u_{gijt} is an unobserved, time-varying shock at the firm level. Workers with a higher supply elasticity will benefit more strongly from changes in firm productivity and therefore have a higher estimated β_g. The regression controls for a firm-specific effect γ_{gi} and a industry-time specific effect γ_{gjt}. The first term captures differential sorting of workers to firm. If high-skill workers sort into firms that share more of the rents with their employees, failing to account for a firm-specific effect would wrongly assign this sorting to bargaining power. The industry-time effect accounts for time-varying productivity shocks at the industry level that also raise wages as they, for instance, raise the demand for all workers in the same industry and therefore increase labor market tightness independently of the performance of the individual firm. The coefficient β_g is therefore estimated from within-firm variation in deviations from industry-wide productivity growth. Two problems with estimating models of that form are measurement error in the explanatory variable and endogeneity. Measurement error in the financial variables biases the estimated elasticity towards zero. I follow Card et al. (2018) and use the growth of sales at the firm in a slightly larger time period, between $t-2$ and t, as an instrument for changes in productivity. The idea is that if measurement error in the longer time period is uncorrelated with measurement error in the shorter time period, then the change in sales in the longer time period can be used as an instrument for the change in value added per worker. While the approach overcomes measurement error, but does not solve endogeneity issues. For instance, if a firm adopts a technology that raises the productivity of high-skill workers, the regression wrongly attributes this to a pass-through of productivity while in reality the worker has become more productive. The results should therefore be taken as suggestive. Nevertheless, to the best of my knowledge,

---

[29]The distinction between marginal and average product is, as far as I am aware, usually not made in this literature.

the present paper is one of very few existing papers that estimate a skill-specific relation between firm productivity and workers' wages[30].

Table 7 shows the estimated elasticities for all skill groups using OLS and IV. The standard errors clustered at the firm level are in parentheses. Figure 13 presents the estimated IV coefficients for each skill type with respective confidence intervals. Using OLS, I find that the elasticity of incumbent wages to firm-level productivity shocks is 0.021 for workers in high-skill occupations and 0.017 for low-skill workers. The differences are economically and statistically small. As expected, when using the instrumental variables, the estimated elasticities increase. In particular, a 10 percent increase in firm productivity raises incumbent high-skill wages by 0.6 percent and low-skill wages by 0.34 percent, and the estimates are statistically different from each other. This is consistent with French high-skill workers capturing a higher share of firm-level rents as estimated by Cahuc et al. (2006). The estimated magnitudes fall into the lower part of the range of existing estimates reported in Card et al. (2018) which lie between 0.05 and 0.15. Moreover, both the IV and OLS estimates reported here are close to the estimates obtained by Card et al. (2018) themselves with Portuguese data. The results suggest that the labor market of high-skill workers is more competitive, allowing them to extract a larger share of rents at the firm than mid- and low-skill workers.

A potential reason for the high-skill labor market being more competitive than the low-skill labor market is worker mobility. If high-skill workers find jobs across a larger geographic area, their employers have to pay them a higher wage in order to keep them. This can be both rationalized in a search model where high-skill workers receive more job offers from firms in other areas, or in a model where high-skill workers have weaker preferences for a short commute or for changing the place of residence to get a better job. Both scenarios imply a more competitive market for high-skill workers. To assess this possibility, I study geographic mobility of workers in France. In particular, I estimate whether highly educated workers migrate more across départements and whether they commute longer distances than less educated workers. For data limitations, I classify workers by education rather than by occupation. I measure annual migration rates in France in the Labor Force Survey waves 1995 to 2002 which is a self-reported indicator of whether the person lived in another département in the previous year. I measure commuting distance in the DADS panel as the distance between the centroids of the municipality of residence and municipality of work[31]. There are 36'000 municipalities in France. They are very small as on average they correspond to a circle of 2 kilometers on average (Combes et al., 2018). I estimate the following regressions

$$y_{igt} = \alpha + \beta_g educ_g + \gamma X_{igt} + u_{igt} \qquad (7.2)$$

where g is the education group of individual i, t is the year when the individual is observed.

---

[30]Card et al. (2015) estimate gender-specific pass-through in Portugal.
[31]For computational reasons, I focus on workrs in the treated and in the matched labor markets.

$educ_g$ are two dummies indicating that the worker has compulsory or secondary education, respectively. X_{igt} is a vector of controls including an indicator for female, a quadratic in age and year fixed effects. y_igt is an indicator of whether the person migrated in the last 12 months, or the log of the commuting distance. As a result, the constant α corresponds to the average migration rate and commuting distance of highly educated workers, and the coefficients β_g estimate whether workers with a lower education are significantly differently mobile from highly educated workers.

Table 8 presents the results. Column 1 shows that 10 percent of highly educated workers migrate every year, while on 6 percent of workers with a secondary or compulsory education do. The differences are statistically significantly different. Similarly, less educated workers commute shorter distances. Compared to highly educated workers, the average commuting distance is 25 percent smaller for workers with a secondary education and 45 percent smaller for workers with a compulsory education. While women do not migrate less, they also commute significantly shorter distances.

The findings presented in this section show evidence consistent with (a) the high-skill labor market being more competitive and (b) that a possible explanation for this is that highly educated workers are more mobile. The results have two implications for how I interpret the positive employment and wage effect of the market integration. First, the improved outside option raises the wages of workers, and more so for workers in less competitive labor markets. Second, the size of the local labor market increases, and more so for workers that are less mobile before the integration. In particular, low-skill workers that search only very locally for jobs get the opportunity of getting more jobs nearby across the border. In contrast, for the high-skill workers this change is proportionally less important because they already receive more job offers from other parts in France. This implies that the labor supply curve to individual French firms in the border region becomes flatter, and the labor market therefore more competitive.

7.2. Heterogeneous effects across firms

To assess whether the supply to individual French firms became more elastic, I now study heterogeneous employment and wage effects of the market integration. For this, I create separate labor market cells defined by industry or by employer type. I study the effect on different types of employers in order to understand whether the market integration increase the competition on the labor market, as discussed in Section 2. In that case, more productive employers should respond with raising wages more. I classify employers by two measures. The first measure – following the literature on rent-sharing (Card et al., 2018) – is labor productivity as measured by value added per worker. Because of the limitation of the firm-level data, I restrict the analysis to single-establishment firms. I then estimate the effect of the market integration separately for firms in the lower and in the upper quintile of the productivity distribution in 1998. The second proxy for firm productivity is firm size (Oi and Idson, 1999), and I group firms into three groups (below

10 employees, 11–49, and above 50).

Figure 12 shows the effect of the market integration on wage growth for firms with high and low productivity. In the first two years after the market integration, wages only rise in highly productive firms, by around 0.7 percent in the first year and by around 1.5 percent after two years. In both cases the effects are statistically significant. In contrast, wages at less productive firms do not rise in the first two years, but only catch up thereafter. This suggests that productive firms had more room to raise wages than less productive firms. The results are similar for large versus small firms. The results are coming soon.

7.3. Alternative explanations

7.3.1. Relative supply and relative wages

The market integration reduced the skill premium in the border area and raised employment of low- and possibly high-skill workers. In a perfectly competitive market where skill groups are imperfect substitutes the reduction in the skill premium could be explained by an increase in the relative supply of high-skill workers. To assess this possibility, I estimate the effect of the market integration on relative supply and relative prices of workers. In particular, I calculate the change in relative supply as $log\frac{L_{h\tau}}{L_{u\tau}} - log\frac{L_{h1998}}{L_{u1998}}$ and the change in relative prices as $\Delta w_{s\tau} - \Delta w_{u\tau}$ where $\Delta w_{g\tau}$ is the cumulative growth in residual wages from 1998 to τ of skill group g. Figure 14 presents the time pattern of the effect on the two outcomes with 95 percent confidence bands around the point estimates. Panel 14a shows the drop in the skill premium of around 2 percent in the medium run after the market integration. In contrast, Panel 14b shows that relative supply of high-skill workers did not increase in the same period. This evidence suggests that the drop in the skill premium cannot be explained by a model where high-skill and low-skill workers are imperfect substitutes and an increase in the relative supply of high-skill workers.

7.3.2. Higher worker productivity

If employers expect low-skill workers to become more abundant after the market integration, they may invest in technologies that make low-skill workers more productive (Acemoglu, 2002). This could raise low-skill wages even if the market is perfectly competitive. I investigate whether the labor market integration made low-skill workers more productive and estimate output elasticities with a Cobb-Douglas production function for firms in the treated and control areas[32]. A firm j in sector s and located in labor market i at time t produces value added y with capital and three labor inputs:

$$y_{jits} = \alpha + x'_{jit}\delta \tag{7.3}$$

[32] An obvious concern is the endogeneity of inputs (Olley and Pakes, 1996). As far as I am aware existing methods that account for this (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015) are not well suited for more than one or two proxy variables. My specification has four state variables and thus requires four proxy variables.

where x'_{jit} is a vector of prodution inputs capital and three skill types (high, mid, low-skill): $x'_{jit} = (k_{jit}, h_{jit}, m_{jit}, l_{jit})'$. I interact all inputs with treatment and time indicators and estimate the following production function:

$$
\begin{aligned}
y_{jits} =& x'_{jit}\delta_0 + post_t \times treat_i \times x'_{jit}\beta_1 + post_t \times x'_{jit}\delta_1 + \\
& treat_t \times x'_{jit}\delta_2 + post_t \times treat_i + \alpha_i + \alpha_t + \alpha_s + u_{jits}
\end{aligned}
\tag{7.4}
$$

where α_i, α_t and α_s account for labor-market, time and two-digit sector fixed effects. u_{jits} is an unobserved productivity shifter. $post_t$ indicates the period after 1998, $treat_i$ indicates treatment labor markets. δ_0 estimates the production function parameters from 1995 to 1998, δ_1 estimates how technology changes after 1998. δ_2 estimates the permanent technological difference between the treatment and the control region. β_1 is the main coefficient of interest and estimates whether the technology changes differentially in the treatment region than in the control region after 1998. If the marginal product of workers increases after 1998 the elements in β_1 should be positive. I cluster the standard errors at the level of departements.

Table 9 presents the results. For brevity I only report the estimated δ_0 and β_1. Column (1) uses the firms from all sectors. The coefficients on the labor inputs interacted with time and treatment are all statistically insignificant. The point estimate is negative and small for high-skill (-0.005, se 0.007) and low-skill workers (-0.006, se 0.003), and positive and larger for mid-skill workers (estimate 0.012, se 0.008). The remaining columns present similar results separately for firms in the tradable, non-tradable, construction and for firms in other sectors. Thus, even if the point estimate is positive for mid-skill workers, the results are inconsistent with higher wages for both mid- and low-skill workers.

7.3.3. Bargaining

A bargaining model could also explain the positive wage effects and there can be two different channels (Beaudry et al., 2012). It would, however, not predict a positive employment effect since workers' improved outside options reduces the job creation of firms and lowers employment.

8. Conclusion

Restrictions to worker mobility can make employers imperfect substitutes for workers. This constrains workers' access to good outside options and increases monopsony power of employers.

Using a quasi-experiment I study the effects of removing barriers to worker mobility. The integration of local labor markets between France and Switzerland provides plausibly exogeneous variation in French workers' access to good jobs. The results suggest that the policy increased wages and employment because of higher competition in the labor market. Several additional pieces of evidence support the interpretation that the market

integration lowered monopsony power, particulary in the low-skill labor market.

The findings have important implications both for labor market policy and for understanding the sources of monopsony power. Enhancing worker mobility can make labor markets more competitive and improve the labor market outcomes, particularly of less-mobile workers. Examples include employer-sponsored health insurance, non-compete agreements or intransferable pension rights. The findings also suggest that larger labor markets are more competitive, consistent with search models or models with differentiation where workers care about a limited set of job characteristics. Understanding better the sources of monopsony power in the labor market and assessing policies that reduce it remain important areas for future research.

References

ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): "High wage workers and high wage firms," *Econometrica*, 67, 251–333.

ACEMOGLU, D. (2002): "Directed technical change," *Review of Economic Studies*, 69, 781–809.

ACKERBERG, D. A., K. CAVES, AND G. FRAZER (2015): "Identification properties of recent production function estimators," *Econometrica*, 83, 2411–2451.

ARNOLD, D. (2019): "Mergers and Acquisitions, Local Labor Market Concentration, and Worker Outcomes," *Working paper*.

ASKENAZY, P. (2013): "Working time regulation in France from 1996 to 2012," *Cambridge Journal of Economics*, 37, 323–347.

BARRAT, O., H. CHAPUT, A. NABOULET, AND L. WOLFF (2007): "Wage bargaining and compensation practices in France: an overview," in *Proceedings of the conference Négociations salariales, emploi, politique économique et monétaire, Banque de France, Paris*.

BEAUDRY, P., D. GREEN, AND B. SAND (2012): "Does Industrial Composition Matter for Wages? A test of Search and Bargaining Theory," *Econometrica*, 80, 1063–1104.

BEAUDRY, P., D. A. GREEN, AND B. M. SAND (2014): "Spatial equilibrium with unemployment and wage bargaining: Theory and estimation," *Journal of Urban Economics*, 79, 2–19.

BEERLI, A., J. RUFFNER, M. SIEGENTHALER, AND G. PERI (2018): "The abolition of immigration restrictions and the performance of firms and workers: Evidence from Switzerland," *NBER Working Paper*.

BELLO, P. AND V. GALASSO (2016): "Old before their time: The role of employers in retirement decisions," Working paper.

BERGER, D. W., K. F. HERKENHOFF, AND S. MONGEY (2019): "Labor Market Power," Tech. rep., National Bureau of Economic Research.

BERRY, S. AND A. PAKES (2007): "The pure characteristics demand model," *International Economic Review*, 48, 1193–1225.

BHASKAR, V., A. MANNING, AND T. TO (2002): "Oligopsony and monopsonistic competition in labor markets," *Journal of Economic Perspectives*, 16, 155–174.

BOAL, W. M., M. R. RANSOM, ET AL. (1997): "Monopsony in the labor market," *Journal of economic literature*, 35, 86–112.

BONTEMPS, C., J.-M. ROBIN, AND G. J. VAN DEN BERG (1999): "An empirical equilibrium job search model with search on the job and heterogeneous workers and firms," *International Economic Review*, 40, 1039–1074.

——— (2000): "Equilibrium search with continuous productivity dispersion: Theory and nonparametric estimation," *International Economic Review*, 41, 305–358.

BUNDESAMT FÜR STATISTIK (2000): "Population census," .

——— (2017): "Lohnstrukturerhebung 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014," .

BUNDESRAT (1999): "Botschaft zur Genehmigung der sektoriellen Abkommen zwischen der Schweiz und der EG," Legal report.

BURDETT, K. AND D. T. MORTENSEN (1998): "Wage differentials, employer size, and unemployment," *International Economic Review*, 257–273.

CAHUC, P., F. POSTEL-VINAY, AND J.-M. ROBIN (2006): "Wage bargaining with on-the-job search: Theory and evidence," *Econometrica*, 74, 323–364.

CALDWELL, S. AND O. DANIELI (2018): "Outside Options in the Labor Market," *Working Paper*.

CALDWELL, S. AND N. HARMON (2018): "Outside Options, Bargaining, and Wages: Evidence from Coworker Networks," *Working paper*.

CAMERON, A. C., J. B. GELBACH, AND D. L. MILLER (2008): "Bootstrap-based improvements for inference with clustered errors," *The Review of Economics and Statistics*, 90, 414–427.

CARD, D., A. R. CARDOSO, J. HEINING, AND P. KLINE (2018): "Firms and labor market inequality: Evidence and some theory," *Journal of Labor Economics*, 36, S13–S70.

CARD, D., A. R. CARDOSO, AND P. KLINE (2015): "Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women," *The Quarterly Journal of Economics*, 131, 633–686.

CARD, D. AND A. KRUEGER (1995): *Myth and Measurement: The new economics of the minimum wage*, Princeton University Press.

COMBES, P.-P., G. DURANTON, AND L. GOBILLON (2018): "The costs of agglomeration: House and land prices in French cities," *The Review of Economic Studies*, 86, 1556–1589.

COMBES, P.-P., G. DURANTON, L. GOBILLON, D. PUGA, AND S. ROUX (2012): "The productivity advantages of large cities: Distinguishing agglomeration from firm selection," *Econometrica*, 80, 2543–2594.

DAVIS, S. J. AND J. HALTIWANGER (2014): "Labor market fluidity and economic performance," Tech. rep., National Bureau of Economic Research.

DI GIOVANNI, J., A. A. LEVCHENKO, AND I. MEJEAN (2014): "Firms, destinations, and aggregate fluctuations," *Econometrica*, 82, 1303–1340.

ECKSTEIN, Z. AND G. J. VAN DEN BERG (2007): "Empirical labor search: A survey," *Journal of Econometrics*, 136, 531–564.

ECKSTEIN, Z. AND K. I. WOLPIN (1990): "Estimating a market equilibrium search model from panel data on individuals," *Econometrica*, 783–808.

EIDGENÖSISCHES AUSSENDEPARTEMENT (EDA) (2016): "Die Schweiz und die Europäische Union," .

ENGBOM, N. AND C. MOSER (2018): "Earnings inequality and the minimum wage: Evidence from Brazil," *Working Paper*, 7, 18–50.

EUROPEAN COMMISSION (1995): Press release 95-118.

FRIEDRICH, B., L. LAUN, C. MEGHIR, AND L. PISTAFERRI (2019): "Earnings dynamics and firm-level shocks," Tech. rep., National Bureau of Economic Research.

GOPINATH, G., Ş. KALEMLI-ÖZCAN, L. KARABARBOUNIS, AND C. VILLEGAS-SANCHEZ (2017): "Capital allocation and productivity in South Europe," *Quarterly Journal of Economics*, 132, 1915–1967.

GOUX, D., E. MAURIN, AND B. PETRONGOLO (2014): "Worktime regulations and spousal labor supply," *American Economic Review*, 104, 252–76.

GREEN, D. A., R. MORISSETTE, B. M. SAND, AND I. SNODDY (2019): "Economy-Wide Spillovers from Booms: Long-Distance Commuting and the Spread of Wage Effects," *Journal of Labor Economics*, 37, S643–S687.

GRUBER, J. (2000): "Health Insurance and the Labor Market," *Handbook of Health Economics*.

HAINMUELLER, J. (2012): "Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies," *Political Analysis*, 20, 25–46.

HARASZTOSI, P. AND A. LINDNER (2019): "Who Pays for the Minimum Wage?" *American Economic Review*, 109, 2693–2727.

HARRIS, J. R. AND M. P. TODARO (1970): "Migration, unemployment and development: a two-sector analysis," *The American Economic Review*, 60, 126–142.

HENNEBERGER, F. AND A. ZIEGLER (2011): "Evaluation der Wirksamkeit der flankierenden Massnahmen zur Personenfreizügigkeit - Teil 2: Überprüfung von Lohndruck aufgrund der Personenfreizügigkeit." *FAA Discussion paper*, 125.

HIRSCH, B., E. J. A. M. JAHN, AND M. OBERFICHTNER (2019): "The urban wage premium in imperfect labour markets," *Working Paper.*

HOFFMANN, F. AND S. SHI (2016): "Burdett–Mortensen model of on-the-job search with two sectors," *Review of Economic Dynamics*, 19, 108–134.

HÄLG, F. (2015): *Technische Handelshemmnisse und die Gewinner tieferer Marktbarrieren*, chap. 4, 113–132, in Schellenbauer and Schwarz (2015).

IMBENS, G. AND M. KOLESAR (2016): "Robust Standard Errors in Small Samples: Some Practical Advice," *Review of Economics and Statistics*, 98, 701–712.

IMBENS, G. W. AND D. B. RUBIN (2015): *Causal inference in statistics, social, and biomedical sciences*, Cambridge University Press.

JÄGER, S., B. SCHOEFER, S. YOUNG, AND J. ZWEIMÜLLER (2018): "Wages and the Value of Nonemployment," *Working paper.*

KAPLOW, L. AND C. SHAPIRO (2007): *Antitrust.*

KATZ, L. F. AND K. M. MURPHY (1992): "Changes in relative wages, 1963–1987: supply and demand factors," *Quarterly Journal of Economics*, 107, 35–78.

KLEINER, M. M. AND A. B. KRUEGER (2013): "Analyzing the extent and influence of occupational licensing on the labor market," *Journal of Labor Economics*, 31, S173–S202.

KLINE, P. AND E. MORETTI (2014): "People, places, and public policy: Some simple welfare economics of local economic development programs," *Annu. Rev. Econ.*, 6, 629–662.

KLINE, P., N. PETKOVA, H. WILLIAMS, AND O. ZIDAR (2019): "Who profits from patents? rent-sharing at innovative firms," *The Quarterly Journal of Economics*, 134, 1343–1404.

LAMADON, T., M. MOGSTAD, AND B. SETZLER (2019): "Imperfect Competition, Compensating Differentials and Rent Sharing in the US Labor Market," Tech. rep., National Bureau of Economic Research.

LEVINSOHN, J. AND A. PETRIN (2003): "Estimating production functions using inputs to control for unobservables," *Review of Economic Studies*, 70, 317–341.

MANNING, A. (2003): *Monopsony in motion: Imperfect competition in labor markets*, Princeton University Press.

MANNING, A. AND B. PETRONGOLO (2017): "How local are labor markets? Evidence from a spatial job search model," *American Economic Review*, 107, 2877–2907.

MIAN, A. AND A. SUFI (2014): "What explains the 2007–2009 drop in employment?" *Econometrica*, 82, 2197–2223.

MONTE, F., S. REDDING, AND E. ROSSI-HANSBERG (2018): "Commuting, migration and local employment elasticities," *American Economic Review*, 108, 3855–90.

MOSCARINI, G. AND F. POSTEL-VINAY (2013): "Stochastic search equilibrium," *Review of Economic Studies*, 80, 1545–1581.

NAIDU, S., Y. NYARKO, AND S.-Y. WANG (2016): "Monopsony power in migrant labor markets: evidence from the United Arab Emirates," *Journal of Political Economy*, 124, 1735–1792.

NEUMARK, D. (2011): "Spurring job creation in response to severe recessions: Reconsidering hiring credits," Tech. rep., National Bureau of Economic Research.

NEUMARK, D. AND W. WASCHER (2010): *Minimum Wages*, MIT Press.

NIMCZIK, J. S. (2018): "Job mobility networks and endogenous labor markets," *Working Paper*.

OECD (2004): "Employment Outlook 2004," .

OI, W. Y. AND T. L. IDSON (1999): "Firm size and wages," *Handbook of labor economics*, 3, 2165–2214.

OLLEY, S. AND A. PAKES (1996): "The dynamics of productivity in the telecommunications equipment industry," *Econometrica*, 64, 1263–1297.

OSTER, E. (2019): "Unobservable selection and coefficient stability: Theory and evidence," *Journal of Business & Economic Statistics*, 37, 187–204.

PROJECT OSRM (2018): "Open Source Routing Machine (OSRM)," http://project-osrm.org/.

Schellenbauer, P. and G. Schwarz, eds. (2015): *Bilateralismus – was sonst*, Verlag Neue Zürcher Zeitung.

Staatsekretariat für Wirtschaft (SECO) (2008): "Die Bilateralen I zwischen der Schweiz und der EU: Eine Zwischenbilanz," *Die Volkswirtschaft*, 81.

Starr, E., J. J. Prescott, and N. Bishara (2019): "Noncompetes in the US labor force," *U of Michigan Law & Econ Research Paper*.

Stuart, E. A. (2010): "Matching methods for causal inference: A review and a look forward," *Statistical Science: a review journal of the Institute of Mathematical Statistics*, 25, 1.

Swiss Federation (1986): "Verordnung über die Begrenzung der Zahl der Ausländer." Legal text.

The Economist (2019): "Another French president tries pension reform," .

Topel, R. H. and M. P. Ward (1992): "Job mobility and the careers of young men," *The Quarterly Journal of Economics*, 107, 439–479.

U.S. Treasury (2016): "Non-compete contracts: Economic Effects and Policy Implications," .

van den Broek, H. (1996): "Switzerland and the European Union," Address at the Swiss-Dutch Chamber of Commerce.

Zhao, Z. (2004): "Using matching to estimate treatment effects: Data requirements, matching metrics, and Monte Carlo evidence," *Review of Economics and Statistics*, 86, 91–107.

9. Figures
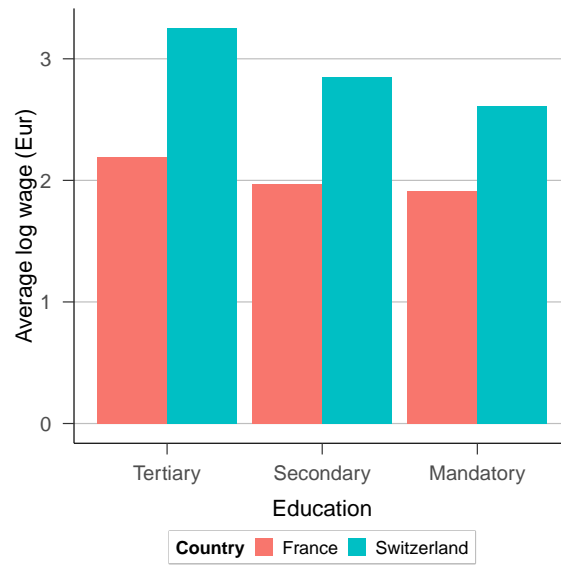
Figure 1: Average wages in the French-Swiss border area in 1998

The figure shows average wages by education group in the labor markets along the border. *Data: DADS Panel, Bundesamt für Statistik (2017).*

(a) All

(b) By education
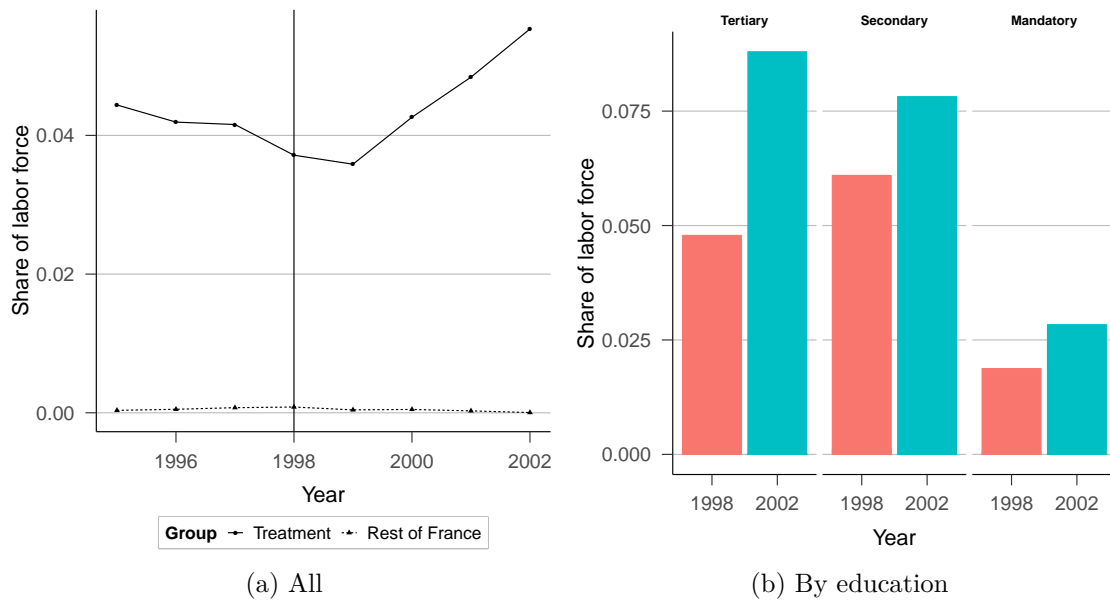
Figure 2: Commuters to Switzerland as share of labor force

The Figures show the number of residents that work in Switzerland as share of the total labor force. The solid line in Panel 2a refers to the treated region, the dashed line to the matched control areas. Panel 2b shows the share for three education groups in 1998 and 2002 in the treatment region. *Data: French Labor Force Survey.*

(a) Residential origin

(b) Transition rates by labor market status
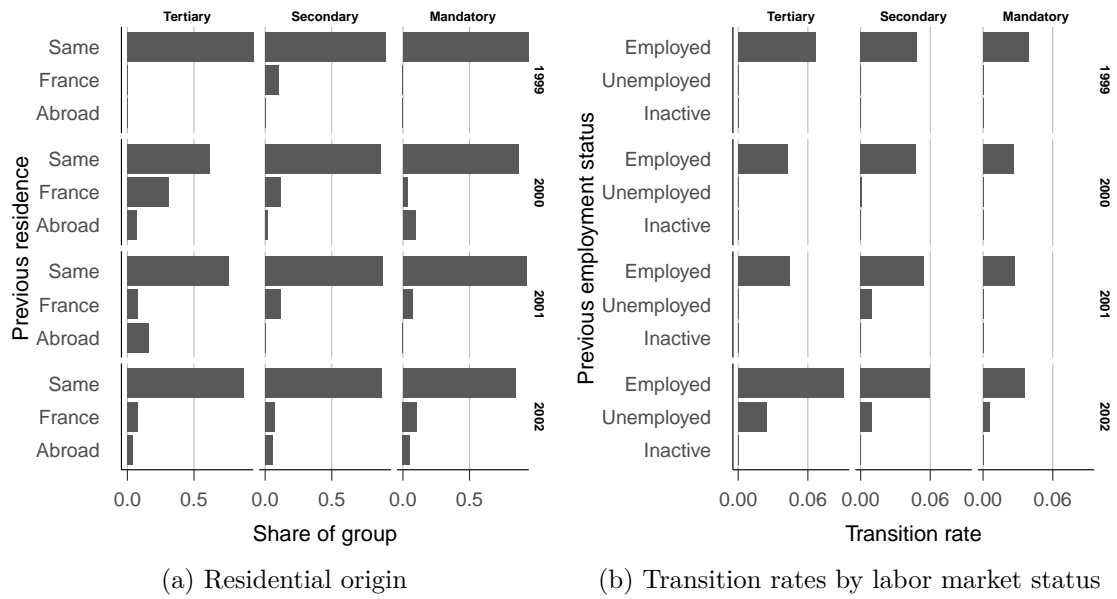
Figure 3: Previous place of residence and labor market status of new border commuters

The data refer to the treatment region. In both panels rows refer to years and columns refer to education groups. Panel 3a shows where the new border commuters came from geographically: whether they lived in the same area, in other parts of France or abroad in the previous year. Panel 3b shows transition rates for people that previously lived in the area by labor force status: Employed, Unemployed, Inactive. *Data: French Labor Force Survey.*

(a) Transition rate by profession

(b) Stayers and new commuters by occupation
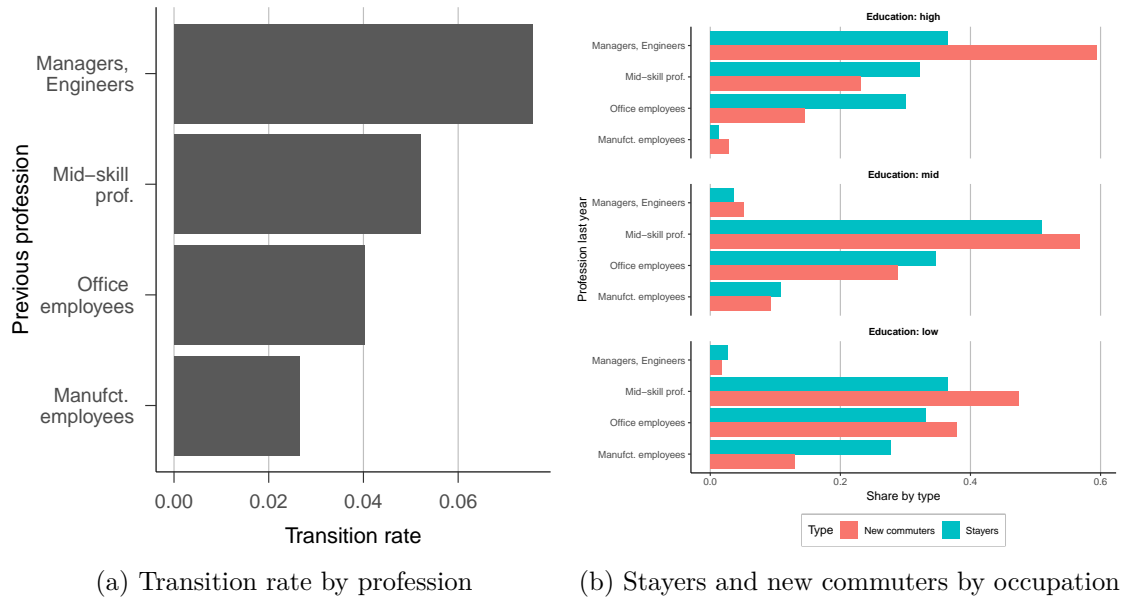
Figure 4: New commuters and their previous profession

The data refer to the treatment region. In both panels "Mid-skill prof." are middle-skill occupatoins such as X and Y and "Manufct. employees" are employees in manufacturing. New border commuters are residents in France that work in Switzerland in the current year but did not do so in the previous year. Panel 4a plots the average transition rates 1999 to 2002 by occupation. Panel 4b shows, by education, the distribution of all stayers and new commuters across their last occupation from 1999 to 2002. Stayers are workers that remain employed in France in two consecutive years. *Data: French Labor Force Survey.*
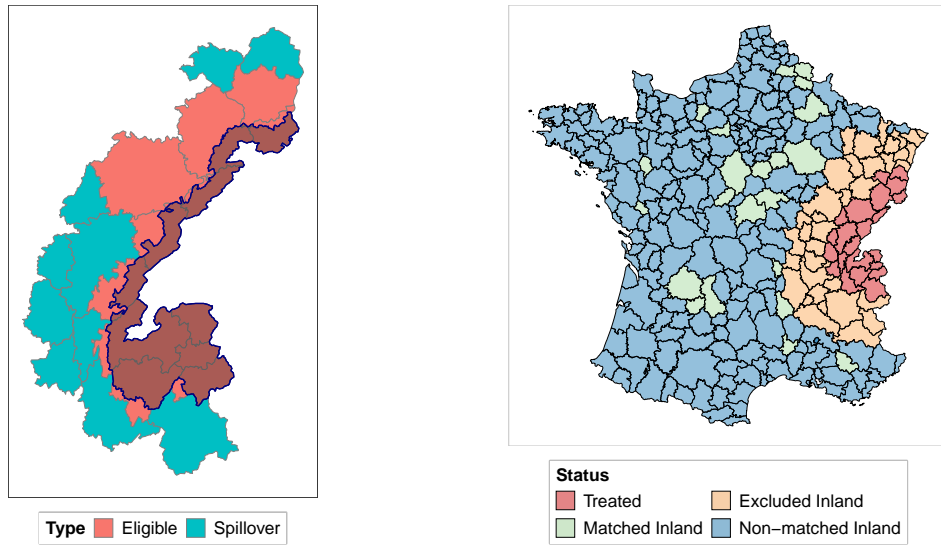
(a) Eligible areas and treatment group   (b) All labor markets and their matching status

Figure 5: Commuting zones in France

Panel 5a shows the treated labor markets. The navy blue area are the municipalities eligible to send commuters. Labor markets are colored by whether they are highly exposed to the market integration (red) by lying directly at the border to Switzerland or less exposed (green). Panel 5b shows all labor markets in France and their matching status. *Border Region* are the treated labor markets. *Excluded Inland* are those not included for the matching strategy. *Matched Inland* and *Non-matched Inland* are the labor markets selected and not selected in the matching procedure. Details: see text.

(a) Normalized Diff. (b) Log Ratio of S.D.
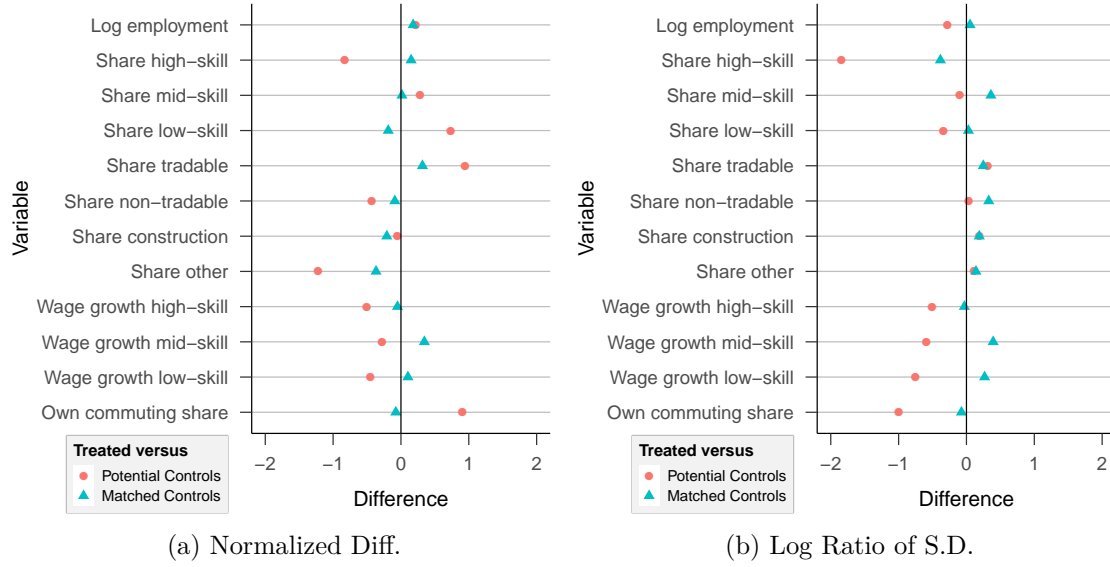
Figure 6: Balance before and after matching

The Figure shows the normalized differences and log ratio of standard deviations between the treatment group and the control group for each variable as indicated on the y-axis. Normalized differences are the differences in means between the treated and the control units, normalized with respect to the standard deviations of the treated and control units. Controls are all potential controls for the red dots and the matched controls for the green diamonds. The variables refer to: log employment, employment share of workers in high, mid and low-skill occupations, employment share in tradable, non-tradable construction and other sector, all in 1998. Wage growth for high, mid and low-skill is cumulative residual wage growth of firm stayers in two consecutive years from 1995 to 1998. Own commuting share is the share of employees in the labor market that also live in that market in 1998. See the Table 1 and text for details.

(a) All workers

(b) High-skill occupations

(c) Mid-skill occupations

(d) Low-skill occupations
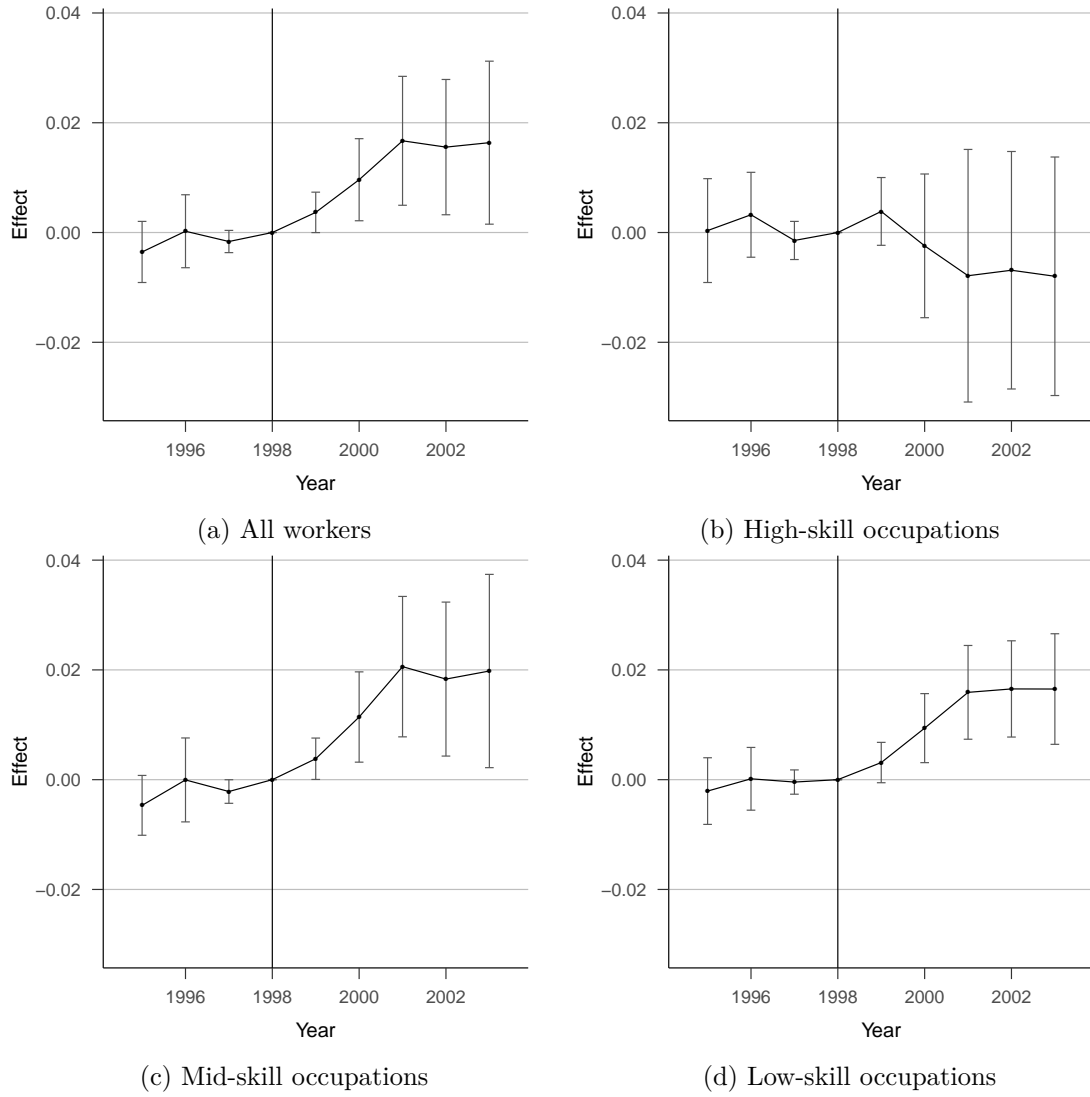
Figure 7: Main effects on wage growth of firm stayers

The figure shows annual estimates of the treatment effect in equation (5.1) on cumulative growth in hourly wages of firm stayers relative to 1998. Regressions are weighted by cell-specific employment in 1998. Hourly wages are residualized for gender and age. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See text for details. *Data: DADS.*

(a) Mid-skill occupations   (b) Low-skill occupations
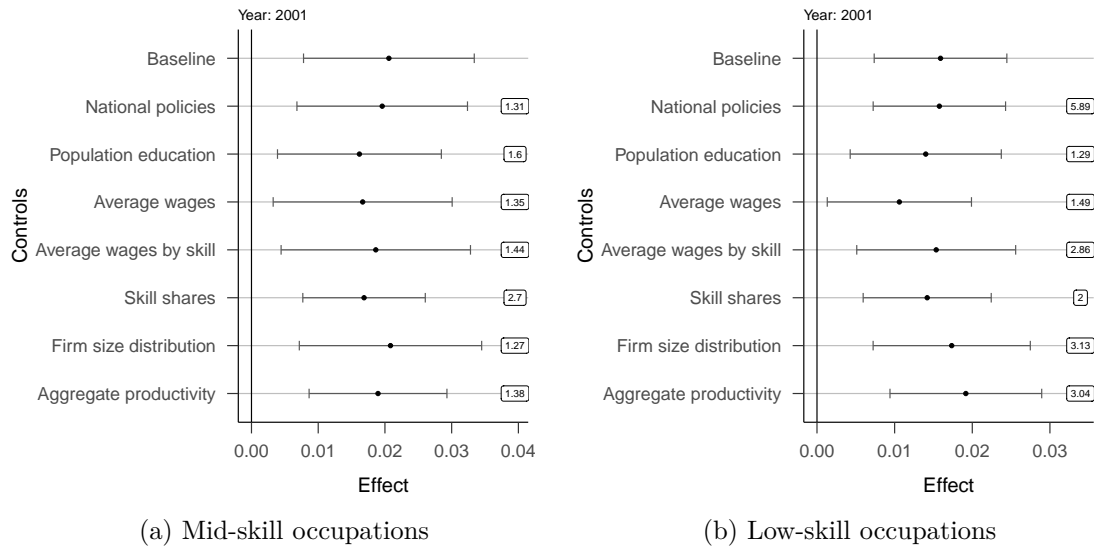
Figure 8: Wage effects for firm stayers when including more controls

The figure shows estimates of the treatment effect in equation (5.1) on cumulative growth in hourly wages of firm stayers relative to 1998. Units are weighted by their skill-specific employment in 1998. Regressions are weighted by cell-specific employment in 1998. *Baseline* shows the baseline effect, *National policies* controls for exposure to minimum wage rises and to the change in workweek legislation, *Population education* controls for population shares of three education groups, *Firm size distribution* controls for employment shares by establishment size, *Aggregate productivity* controls for value added and capital per worker. The number in the box on the right of the error bars shows the amount of unobservable selection compared to observable selection necessary to drive the estimated effect to zero (Oster, 2019). See the text for details. *Data: DADS, Ficus*

(a) All workers

(b) High-skill occupations

(c) Mid-skill occupations

(d) Low-skill occupations
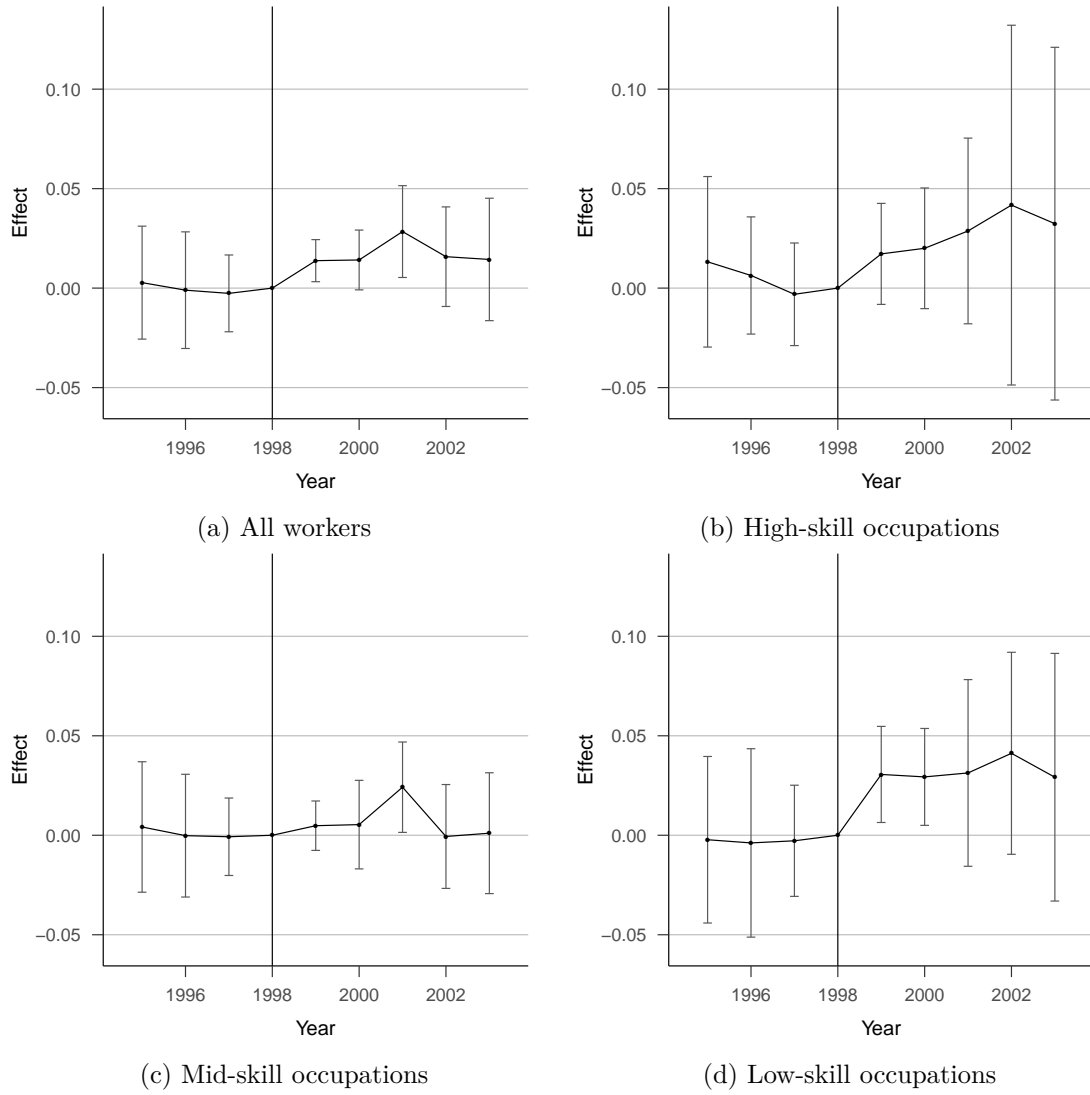
Figure 9: Main effects on total employment

The figure shows annual estimates of the treatment effect in equation (5.1) on total employment. Regressions are weighted by cell-specific employment in 1998. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See text for details. *Data: DADS.*

(a) All workers

(b) High-skill occupations

(c) Mid-skill occupations

(d) Low-skill occupations
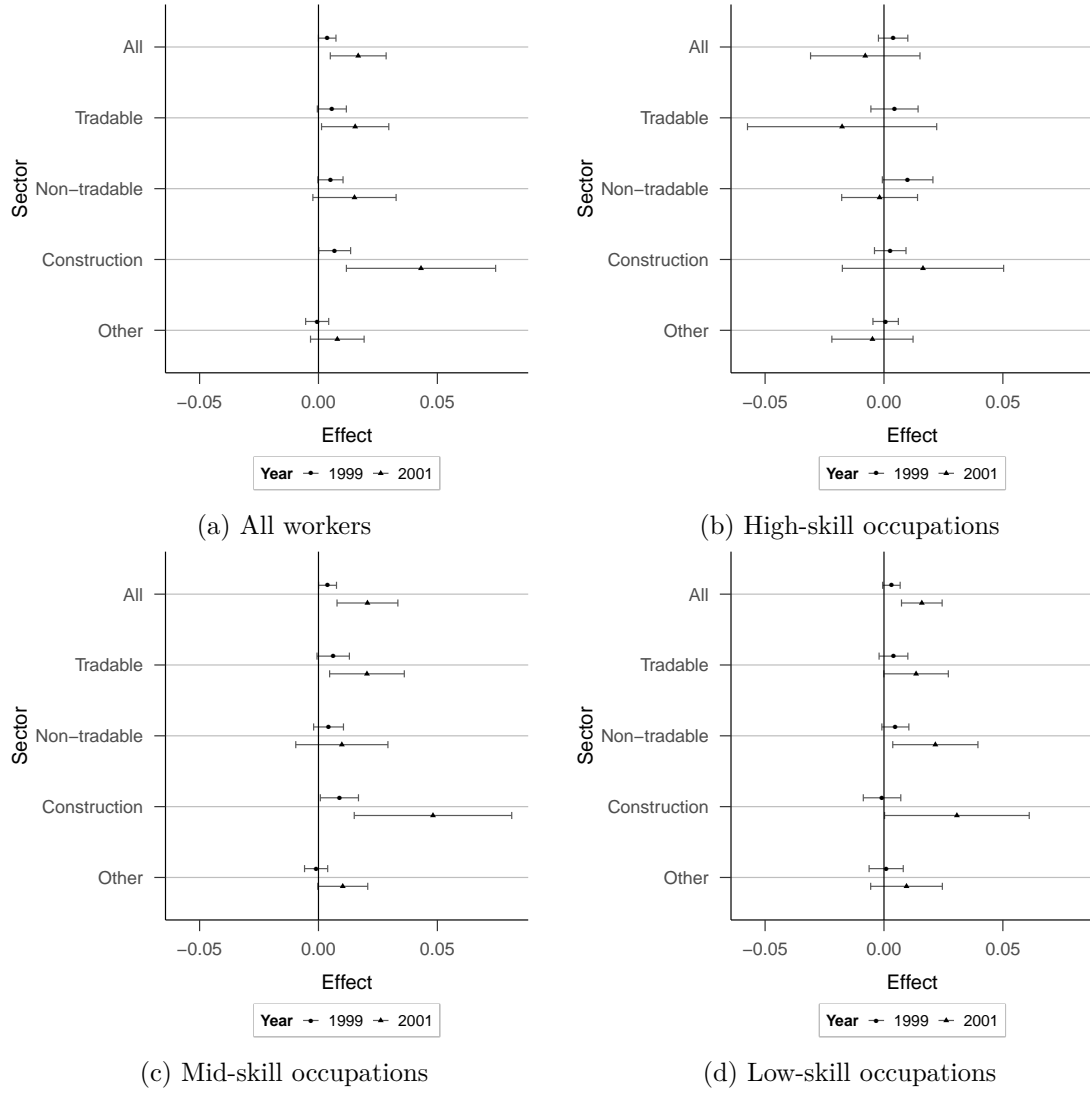
Figure 10: Wage effects across industries

The figure shows annual estimates of the treatment effect in equation (5.1) on wages in different industries. Regressions are weighted by cell-specific employment in 1998. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See text for details. *Data: DADS.*

(a) High-skill occupations　　　　　(b) Low-skill occupations
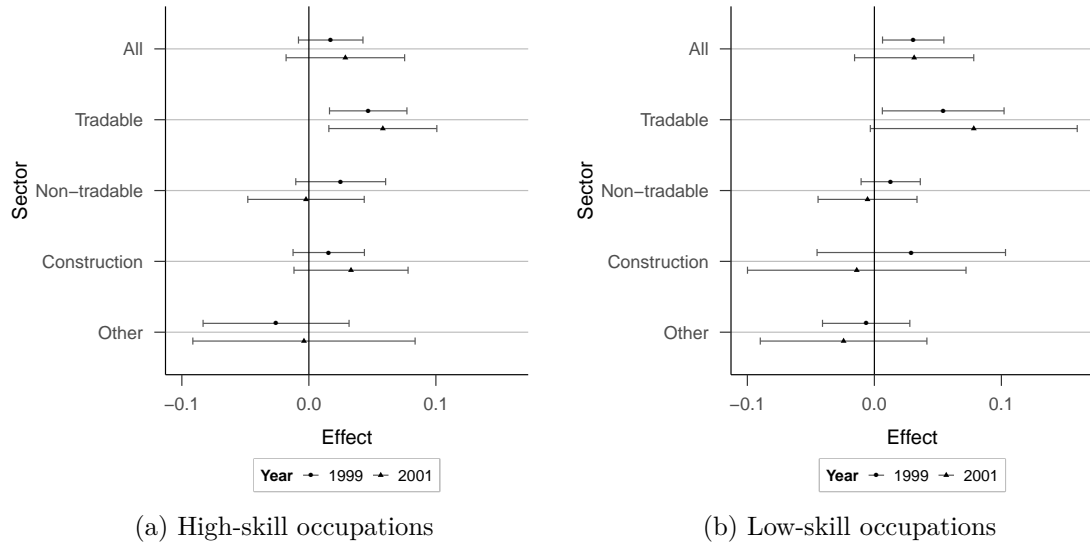
Figure 11: Employment effects across industries

The figure shows annual estimates of the treatment effect in equation (5.1) on employment in different industries. Regressions are weighted by cell-specific employment in 1998. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See text for details. *Data: DADS.*

(a) Wage growth by firm productivity
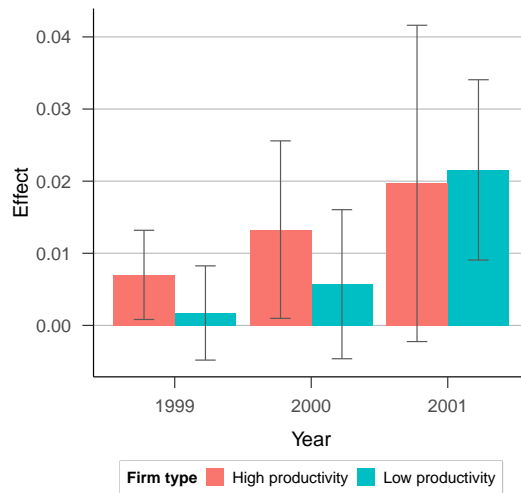
Figure 12: Wage effects by firm productivity

The figure shows annual estimates of the treatment effect in equation (5.1) on wages in with high and low productivity firms with a single establishment. Regressions are weighted by employment in 1998. High-productivity (low-productivity) firms are firms in the upper (lower) quintile of the labor-market specific productivity distribution. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See text for details. *Data: DADS, Ficus.*
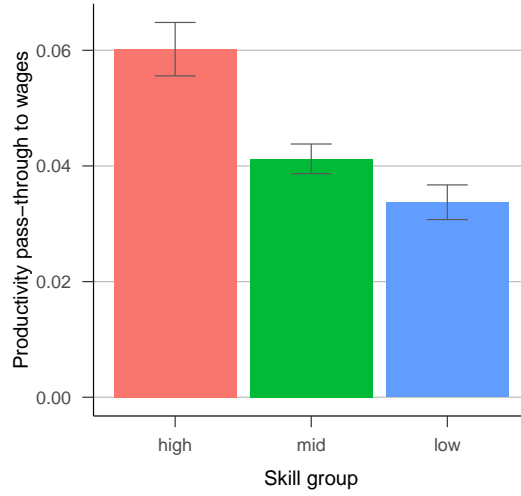
Figure 13: Pass-through of wages to productivity by skill group

The figure shows the results from estimating equation (7.1) for single-establishment firms, using sales growth in the two previous years as an instrument. The regressions are estimated for each skill group separately and weighted by the number of employees in each year. The error bars show the 95% intervals around the point estimate using standard errors clustered at the firm level. See text for details. *Data: DADS, Ficus.*

(a) Effect on relative wages

(b) Effect on relative supply
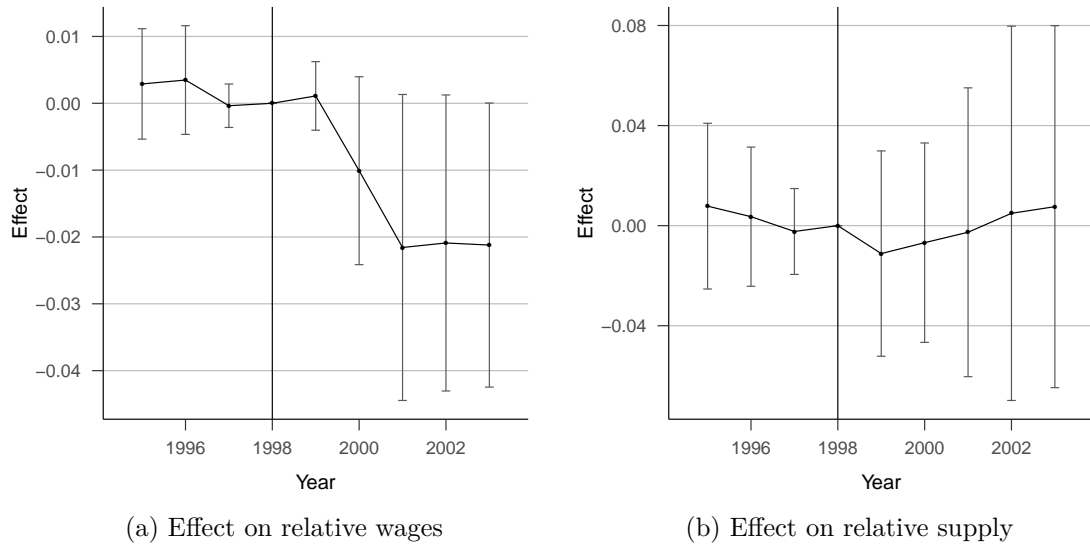
Figure 14: Effect on relative wages and relative supply

The figure shows annual estimates of the treatment effect in equation (5.1) on relative supply and relative wages in the border area. Relative wages is the difference in cumulative wage growth since 1998 between high- and low-skill workers. Relative supply is the change in the log ratio of high- versus low-skill supply. Regressions are weighted by total employment in 1998. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See text for details. *Data: DADS.*

10. Tables

|	Controls		Treated		Overlap measures			
	Mean	(S.D.)	Mean	(S.D.)	Nor Dif	Log ratio SD	pi c	pi t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controls: All								
Log employment	10.53	(1.05)	10.74	(0.79)	0.22	−0.28	0.13	0.00
Share high-skill	0.14	(0.08)	0.10	(0.01)	−0.83	−1.84	0.30	0.00
Share mid-skill	0.61	(0.04)	0.62	(0.04)	0.28	−0.10	0.07	0.00
Share low-skill	0.24	(0.06)	0.28	(0.04)	0.73	−0.34	0.12	0.00
Share tradable	0.40	(0.08)	0.50	(0.11)	0.94	0.31	0.05	0.18
Share non-tradable	0.13	(0.03)	0.12	(0.03)	−0.43	0.03	0.10	0.14
Share construction	0.11	(0.02)	0.10	(0.02)	−0.05	0.19	0.06	0.14
Share other	0.36	(0.06)	0.28	(0.07)	−1.22	0.11	0.08	0.14
Wage growth high-skill	0.07	(0.02)	0.06	(0.01)	−0.51	−0.51	0.12	0.00
Wage growth mid-skill	0.07	(0.02)	0.07	(0.01)	−0.28	−0.59	0.17	0.00
Wage growth low-skill	0.07	(0.02)	0.06	(0.01)	−0.45	−0.75	0.23	0.00
Own commuting share	0.74	(0.15)	0.85	(0.06)	0.90	−1.00	0.15	0.05
Overall distance across covariates					1.18			
N	238.00		22.00					
Panel B. Controls: Matched								
Log employment	10.57	(0.75)	10.74	(0.79)	0.18	0.05	0.05	0.05
Share high-skill	0.09	(0.02)	0.10	(0.01)	0.15	−0.38	0.18	0.09
Share mid-skill	0.62	(0.03)	0.62	(0.04)	0.01	0.36	0.00	0.14
Share low-skill	0.29	(0.04)	0.28	(0.04)	−0.19	0.03	0.00	0.14
Share tradable	0.47	(0.09)	0.50	(0.11)	0.32	0.25	0.00	0.14
Share non-tradable	0.12	(0.02)	0.12	(0.03)	−0.09	0.33	0.05	0.14
Share construction	0.11	(0.02)	0.10	(0.02)	−0.21	0.19	0.09	0.00
Share other	0.31	(0.06)	0.28	(0.07)	−0.37	0.14	0.05	0.09
Wage growth high-skill	0.06	(0.02)	0.06	(0.01)	−0.05	−0.03	0.05	0.05
Wage growth mid-skill	0.06	(0.01)	0.07	(0.01)	0.34	0.39	0.00	0.18
Wage growth low-skill	0.06	(0.01)	0.06	(0.01)	0.10	0.27	0.00	0.18
Own commuting share	0.86	(0.06)	0.85	(0.06)	−0.08	−0.07	0.09	0.00
Overall distance across covariates					0.22			
N	22.00		22.00					

The table shows balancing statistics between treatment and control for two samples. In Panel A controls are all potential controls. In Panel B controls are the matched controls. The overlap measures are: normalized differences, log ratios of standard deviations, and pi for control and treated units. Normalized differences use the population standard deviation in the full sample in the denominator. pi measures the probability mass of units of the treatment (control) group that lie outside the interval between the 0.025th and 0.975th quantile of the control (treatment) group. The overall distance is the variance-weighted difference between the vector of means for the treated and for the control group. See Section 5.2 for details

Table 1: Balance before and after matching

	Wages		Employment	
	Short-run	Medium-run	Short-run	Medium-run
	(1)	(2)	(3)	(4)
Panel A: All				
beta	0.004	0.017	0.014	0.028
	(0.002)	(0.006)	(0.005)	(0.012)
	[0.092]	[0.021]	[0.034]	[0.022]
N	44	44	44	44
Adj. R-squared	0.075	0.267	0.126	0.155
Panel B: High-skill				
beta	0.004	-0.008	0.017	0.029
	(0.003)	(0.012)	(0.013)	(0.024)
	[0.237]	[0.546]	[0.232]	[0.278]
N	44	44	44	44
Adj. R-squared	0.035	0	0.05	0.053
Panel C: Mid-skill				
beta	0.004	0.021	0.005	0.024
	(0.002)	(0.007)	(0.006)	(0.012)
	[0.084]	[0.01]	[0.452]	[0.051]
N	44	44	44	44
Adj. R-squared	0.059	0.313	-0.015	0.058
Panel D: Low-skill				
beta	0.003	0.016	0.031	0.031
	(0.002)	(0.004)	(0.012)	(0.024)
	[0.129]	[0.008]	[0.032]	[0.215]
N	44	44	44	44
Adj. R-squared	0.046	0.242	0.101	0.035

Standard errors robust to clustering at the department level are in parentheses, and wild-cluster bootstrapped p-values in brackets. The columns present results from estimating equation (5.1) for different years. Short-run refers to year 1999 , medium-run to year 2001 . Wages are the cumulative residual wage growth since 1998. Employment is the change in aggregate log employment. Regressions are weighted by skill-specific employment in 1998. Details: see text. *Data: DADS.*

Table 2: Main effects on wages and employment

Table 3: Main effects by sector

	Wages: Medium-run					Employment: Medium-run				
	Baseline	Tradable	Non-Tradable	Cons-truction	Other	Baseline	Tradable	Non-Tradable	Cons-truction	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A: All										
beta	0.017	0.015	0.015	0.043	0.008	0.028	0.048	0.011	-0.01	0.02
	(0.006)	(0.007)	(0.009)	(0.016)	(0.006)	(0.012)	(0.022)	(0.014)	(0.019)	(0.016)
	[0.021]	[0.053]	[0.128]	[0.019]	[0.223]	[0.022]	[0.058]	[0.452]	[0.593]	[0.251]
N	44	44	44	44	44	44	44	44	44	44
Adj. R-squared	0.267	0.127	0.07	0.291	0.048	0.155	0.124	-0.004	-0.013	0.026
B: High										
beta	-0.008	-0.018	-0.002	0.016	-0.005	0.029	0.058	-0.002	0.033	-0.004
	(0.012)	(0.02)	(0.008)	(0.017)	(0.009)	(0.024)	(0.022)	(0.023)	(0.023)	(0.045)
	[0.546]	[0.446]	[0.823]	[0.377]	[0.677]	[0.278]	[0.011]	[0.922]	[0.15]	[0.954]
N	44	44	44	44	44	44	44	44	44	44
Adj. R-squared	0	0.014	-0.023	0.024	-0.008	0.053	0.152	-0.024	0.019	-0.023
C: Mid										
beta	0.021	0.02	0.01	0.048	0.01	0.024	0.031	0.041	-0.01	0.027
	(0.007)	(0.008)	(0.01)	(0.017)	(0.005)	(0.012)	(0.022)	(0.025)	(0.019)	(0.012)
	[0.01]	[0.026]	[0.341]	[0.013]	[0.083]	[0.051]	[0.184]	[0.159]	[0.6]	[0.068]
N	44	44	44	44	44	44	44	44	44	44
Adj. R-squared	0.313	0.169	0.012	0.303	0.094	0.058	0.021	0.051	-0.013	0.073
D: Low										
beta	0.016	0.014	0.022	0.031	0.009	0.031	0.078	-0.005	-0.014	-0.024
	(0.004)	(0.007)	(0.009)	(0.016)	(0.008)	(0.024)	(0.042)	(0.02)	(0.044)	(0.033)
	[0.008]	[0.077]	[0.057]	[0.069]	[0.246]	[0.215]	[0.081]	[0.8]	[0.758]	[0.532]
N	44	44	44	44	44	44	44	44	44	44
Adj. R-squared	0.242	0.064	0.132	0.157	0.023	0.035	0.097	-0.021	-0.022	-0.006

Standard errors clustered at the department level are in parentheses, and wild-cluster bootstrapped p-values in brackets. The columns present results on wage growth and employment in year 2001 . Regressions are weighted by cell-specific employment in 1998. *Baseline* is the baseline regression with all sectors, *Tradable* are tradable sectors, *Non-tradable* are local non-tradable services, *Construction* are construction industries, *Other* are other industries. Tradable sectors are classified as in Combes et al. (2012) and include manufacturing and business services. Non-tradable, construction and other sectors are classified as in Mian and Sufi (2014). See text for details. *Data: DADS.*

	Wages: Short-run				Wages: Medium-run			
	Baseline	National Policies	Avg. wages	Avg. wages, by skill	Baseline	National Policies	Avg. wages	Avg. wages, by skill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All								
beta	0.004	0.004	0.002	0.004	0.017	0.016	0.012	0.014
	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
	[0.092]	[0.065]	[0.284]	[0.088]	[0.021]	[0.028]	[0.056]	[0.052]
N	44	44	44	44	44	44	44	44
Adj. R-squared	0.075	0.154	0.117	0.174	0.267	0.261	0.399	0.387
Panel B: High-skill								
beta	0.004	0.004	0.002	0.003	-0.008	-0.01	-0.017	-0.023
	(0.003)	(0.003)	(0.003)	(0.003)	(0.012)	(0.012)	(0.01)	(0.012)
	[0.237]	[0.232]	[0.52]	[0.337]	[0.546]	[0.494]	[0.217]	[0.246]
N	44	44	44	44	44	44	44	44
Adj. R-squared	0.035	0.058	0.108	0.065	0	-0.015	0.174	0.232
Panel C: Mid-skill								
beta	0.004	0.004	0.003	0.005	0.021	0.02	0.017	0.019
	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
	[0.084]	[0.083]	[0.247]	[0.075]	[0.01]	[0.016]	[0.016]	[0.026]
N	44	44	44	44	44	44	44	44
Adj. R-squared	0.059	0.073	0.052	0.124	0.313	0.294	0.366	0.351
Panel D: Low-skill								
beta	0.003	0.003	0.001	0.003	0.016	0.016	0.011	0.015
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
	[0.129]	[0.04]	[0.454]	[0.094]	[0.008]	[0.001]	[0.012]	[0.002]
N	44	44	44	44	44	44	44	44
Adj. R-squared	0.046	0.2	0.141	0.171	0.242	0.329	0.353	0.437

Standard errors robust to clustering at the department level are in parentheses, and wild-cluster bootstrapped p-values in brackets. The columns present results from estimating equation (5.1) for different years. Short-run refers to year 1999 , medium-run to year 2001 . *Baseline* is the main specification *National policies* controls for exposure to minimum wage changes, *Average wages* controls for average residual log wages in 1998, *Average wages, by skill* controls for skill-specific residual log wages in 1998. Wages are the cumulative residual wage growth since 1998. Employment is the change in aggregate log employment. Regressions are weighted by skill-specific employment in 1998. Details: see text. *Data: DADS.*

Table 4: Robustness of main effects: Wages

	Employment: Short-run				Employment: Medium-run			
	Baseline	National Policies	Avg. wages	Avg. wages, by skill	Baseline	National Policies	Avg. wages	Avg. wages, by skill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All								
beta	0.014	0.013	0.016	0.017	0.028	0.028	0.033	0.037
	(0.005)	(0.006)	(0.006)	(0.007)	(0.012)	(0.012)	(0.012)	(0.016)
	[0.034]	[0.049]	[0.047]	[0.07]	[0.022]	[0.03]	[0.021]	[0.063]
N	44	44	44	44	44	44	44	44
Adj. R-squared	0.126	0.12	0.126	0.145	0.155	0.126	0.164	0.168
Panel B: High-skill								
beta	0.017	0.014	0.01	0.019	0.029	0.025	0.017	0.036
	(0.013)	(0.014)	(0.015)	(0.019)	(0.024)	(0.024)	(0.028)	(0.03)
	[0.232]	[0.339]	[0.572]	[0.476]	[0.278]	[0.343]	[0.597]	[0.323]
N	44	44	44	44	44	44	44	44
Adj. R-squared	0.05	0.16	0.122	0.135	0.053	0.193	0.122	0.179
Panel C: Mid-skill								
beta	0.005	0.006	0.009	0.012	0.024	0.027	0.033	0.037
	(0.006)	(0.006)	(0.007)	(0.008)	(0.012)	(0.011)	(0.013)	(0.014)
	[0.452]	[0.377]	[0.232]	[0.218]	[0.051]	[0.02]	[0.018]	[0.037]
N	44	44	44	44	44	44	44	44
Adj. R-squared	-0.015	-0.059	-0.003	0.018	0.058	0.046	0.093	0.092
Panel D: Low-skill								
beta	0.031	0.027	0.035	0.027	0.031	0.027	0.041	0.038
	(0.012)	(0.011)	(0.014)	(0.013)	(0.024)	(0.025)	(0.022)	(0.032)
	[0.032]	[0.038]	[0.038]	[0.081]	[0.215]	[0.366]	[0.124]	[0.389]
N	44	44	44	44	44	44	44	44
Adj. R-squared	0.101	0.166	0.092	0.105	0.035	0.027	0.038	0.021

Standard errors robust to clustering at the department level are in parentheses, and wild-cluster bootstrapped p-values in brackets. The columns present results from estimating equation (5.1) for different years. Short-run refers to year 1999 , medium-run to year 2001 . *Baseline* is the main specificion *National policies* controls for exposure to minimum wage changes, *Average wages* controls for average residual log wages in 1998, *Average wages, by skill* controls for for skill-specific residual log wages in 1998. Wages are the cumulative residual wage growth since 1998. Employment is the change in aggregate log employment. Regressions are weighted by skill-specific employment in 1998. Details: see text. *Data: DADS.*

Table 5: Robustness of main effects: Employment

Outcome:	Wages, 1998-2001			Employment, 1998-2001		
	Baseline	Tradable	Tradable w/o trade reform	Baseline	Tradable	Tradable w/o trade reform
	(1)	(2)	(3)	(4)	(5)	(6)
A: All						
beta	0.017	0.015	0.018	0.028	0.048	0.051
	(0.006)	(0.007)	(0.008)	(0.012)	(0.022)	(0.031)
	[0.021]	[0.053]	[0.02]	[0.022]	[0.058]	[0.166]
N	44	44	44	44	44	44
Adj. R-squared	0.267	0.127	0.117	0.155	0.124	0.088
B: Mid						
beta	0.021	0.02	0.019	0.024	0.031	0.036
	(0.007)	(0.008)	(0.009)	(0.012)	(0.022)	(0.025)
	[0.01]	[0.026]	[0.024]	[0.051]	[0.184]	[0.202]
N	44	44	44	44	44	44
Adj. R-squared	0.313	0.169	0.086	0.058	0.021	0.031
C: Low						
beta	0.016	0.014	0.019	0.031	0.078	0.089
	(0.004)	(0.007)	(0.005)	(0.024)	(0.042)	(0.06)
	[0.008]	[0.077]	[0.001]	[0.215]	[0.081]	[0.191]
N	44	44	44	44	44	44
Adj. R-squared	0.242	0.064	0.195	0.035	0.097	0.071

Standard errors clustered at the department level are in parentheses, and wild-cluster bootstrapped p-values in brackets. The columns present results on wage growth and employment in year 2001 . Regressions are weighted by cell-specific employment in 1998. Columns (1) and (4) are the baseline with the complete sample, Columns (2) and (4) only include the tradable sector, and Columns (3) and (6) only include tradable industries not affected by the reduction in the fixed cost of trade. Tradable sector is defined as in Combes et al. (2012) and includes manufacturing and business services. Four-digit sectors affected by the trade reform are taken from Bello and Galasso (2016). See text for details. *Data: DADS.*

Table 6: Main effects, dropping sectors with trade reform

Outcome: Wage growth	High-skill		Mid-skill		Low-skill	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Productivity growth	0.021	0.06	0.019	0.041	0.017	0.034
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
N (firm x year)	1657432	1657432	3722567	3722567	2411195	2411195
R-squared	0.292	0.284	0.24	0.235	0.277	0.275
First stage coefficient		0.362		0.363		0.377
		(0.004)		(0.003)		(0.004)
Firm FE	Y	Y	Y	Y	Y	Y
Industry-time FE	Y	Y	Y	Y	Y	Y

Regressions of incumbent wage growth on firm productivity growth. Standard errors clusted by firm in parentheses. The unit of observation is the firm-skill group-year, and regressions are weighted by the number of firm stayers in that cell. The sample includes firms with non-zero stayers in two consecutive and complete balance sheet information in the two preceding years. Finacial variables are winsorized at the 1% and 99% level in each year. The instrument is sales growth per worker in the previous two years. OLS = Ordinary Least Squares, IV = Instrumental variables. *Data: DADS Postes, Ficus.*

Table 7: Wages and productivity

	P[migrate]	Commuting
	(1)	(2)
Constant	0.1	5.42
	(0.002)	(0.438)
Medium education	-0.04	-0.29
	(0.001)	(0.123)
Low education	-0.04	-0.59
	(0.001)	(0.147)
Female	0	-0.68
	(0)	(0.093)
N	747607	83283
R2	0.01	0.01

Column (1) reports the result from a linear probability model of the annual migration rate. Standard errors are robust to heteroskedasticity. In Column (2) the outcome is $\log(1 + \text{commuting distance})$, and standard errors are clustered at the labor market level. Commuting distance is measured between centroids of municipality of work and municipality of residence. See text for details. *Data: LFS, DADS Panel*

Table 8: Worker mobility

	All	Tradable	Non-tradable	Construction	Other
	(1)	(2)	(3)	(4)	(5)
Intercept	1.738	1.666	2.205	2.228	2.35
	(0.018)	(0.027)	(0.049)	(0.044)	(0.103)
k	0.205	0.171	0.268	0.149	0.19
	(0.006)	(0.008)	(0.01)	(0.008)	(0.008)
h	0.215	0.248	0.169	0.232	0.225
	(0.008)	(0.012)	(0.01)	(0.015)	(0.011)
m	0.358	0.373	0.267	0.442	0.378
	(0.007)	(0.012)	(0.012)	(0.012)	(0.012)
l	0.131	0.152	0.16	0.106	0.111
	(0.004)	(0.007)	(0.005)	(0.004)	(0.008)
k x post x treat	0.003	0.008	0.021	0.011	-0.005
	(0.006)	(0.01)	(0.011)	(0.014)	(0.016)
h x post x treat	-0.005	-0.015	0.008	-0.012	-0.005
	(0.007)	(0.014)	(0.013)	(0.015)	(0.013)
m x post x treat	0.012	0.005	0	0.001	0.027
	(0.008)	(0.015)	(0.012)	(0.014)	(0.013)
l x post x treat	-0.006	-0.007	0.004	-0.012	-0.013
	(0.003)	(0.006)	(0.009)	(0.007)	(0.011)
N (firm x year)	181287	67224	41911	31632	40520
R-squared	0.852	0.881	0.758	0.873	0.812

Results from estimating equation (7.4). Standard errors clustered at the department level are in parentheses. The columns refer to sectors: (1) – All sectors, (2) – Tradable sector, (3) – Non-tradable sectors, (4) – Construction sector (5) – Other sectors. The coefficients are: K – capital, H – high-skill labor, M – mid-skill labor, L – low-skill labor and the double-interaction with treatment status and year after 1998. Single-interactions with treatment and with post are not reported for brevity. The number of observations refer to firm-year observations. Sample: single-establishment firms with positive inputs and outputs. See text for details. *Data: Ficus.*

Table 9: Results from production functions

A. Additional figures

A.1. Descriptive analysis

Figure A1 illustrates the situation in labor markets along the French-Swiss border in 1998. The units are local labor markets as defined by the statistical offices of the two countries. The colors refer to quantiles of the distribution of the variable depicted[33]. Panel A1a shows the employment density per square kilometer. French labor markets along the border are less dense than their Swiss neighbors. There are two Swiss cities in the west (Geneva) and in the north (Basel). Panel A1b shows the travel time by car from French labor markets to Switzerland. The time is the population-weighted average time between all municipalities in the labor market and their closest border crossing to Switzerland. Travel times are sourced from Project OSRM (2018), refer to 2018 and are net of congestion time. Labor markets immediately at the border are between 13 and 33 minutes away from the next border crossing to Switzerland. The maximum time to the next border crossing is 96 minutes. Panel A1c plots mean log wages in the labor markets. Wages change discontinuously at the border: average wages in France are lower than in Switzerland. Panels A1d to A1f show the wages by education level and labor market. The numbers in the panels by labor market and education should be interpreted with caution because some of them rely on a small number of observations.

---

[33]The light blue areas are lakes.

Mean log wages (EUR), all
In the affected region in 1998

Quantile

1.9–2	2–2.63	2.63–2.77
2.77–2.84	2.84–3.07	

(c) Average wages

Mean travel time
To next Swiss border crossing (minutes)

Quantile

13–27	27–33	33–55
55–75	75–96	

(b) Travel time (car) to the next border crossing

Employment density
In the affected region in 1998

Quantile

1.5–9.7	9.7–15.2	15.2–28.7
28.7–44.3	44.3–1339	

(a) Employment density

Mean log wages (EUR), education: low
In the affected region in 1998

Quantile

1.74–1.92	1.92–2.44	2.44–2.56
2.56–2.64	2.64–2.77	

(f) Wages, Compulsory education or less

Mean log wages (EUR), education: mid
In the affected region in 1998

Quantile

1.84–2	2–2.66	2.66–2.76
2.76–2.82	2.82–3.03	

(e) Wages, Secondary education

Mean log wages (EUR), education: high
In the affected region in 1998

Quantile

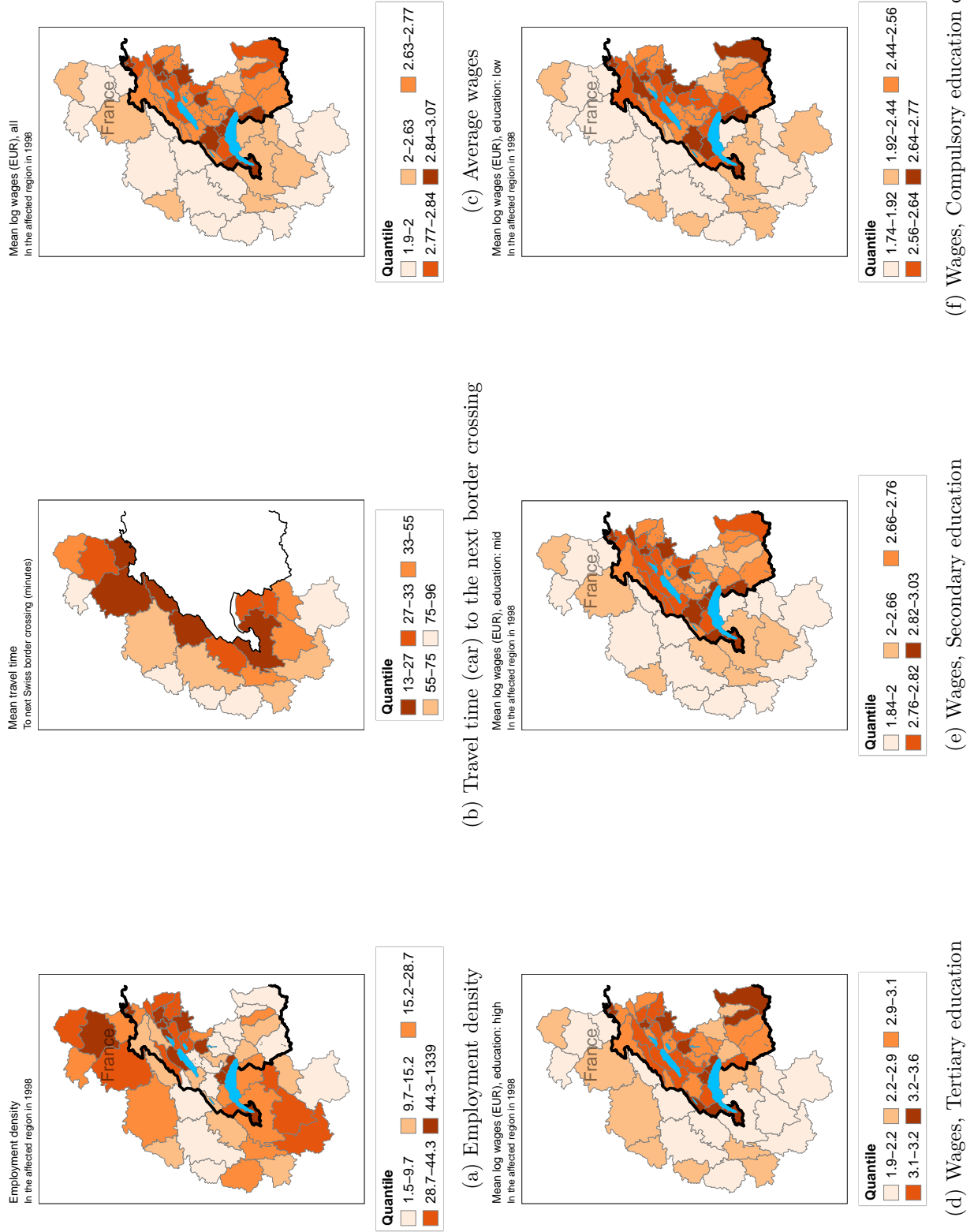|		
1.9–2.2	2.2–2.9	2.9–3.1
3.1–3.2	3.2–3.6	

(d) Wages, Tertiary education

Figure A1: Labor markets at the border in 1998

The black solid line in all panels is the border between Switzerland and France. Colors refer to quantiles. Panel A1a shows employment per square kilometer in 1998. Panel A1b plots the mean travel time (minutes) to the next border crossing. The mean is calculated as the population-weighted average time between a municipality's centroid and the next border crossing to Switzerland. Travel times are for car

50

(a) All workers

(b) High-skill occupations

(c) Mid-skill occupations
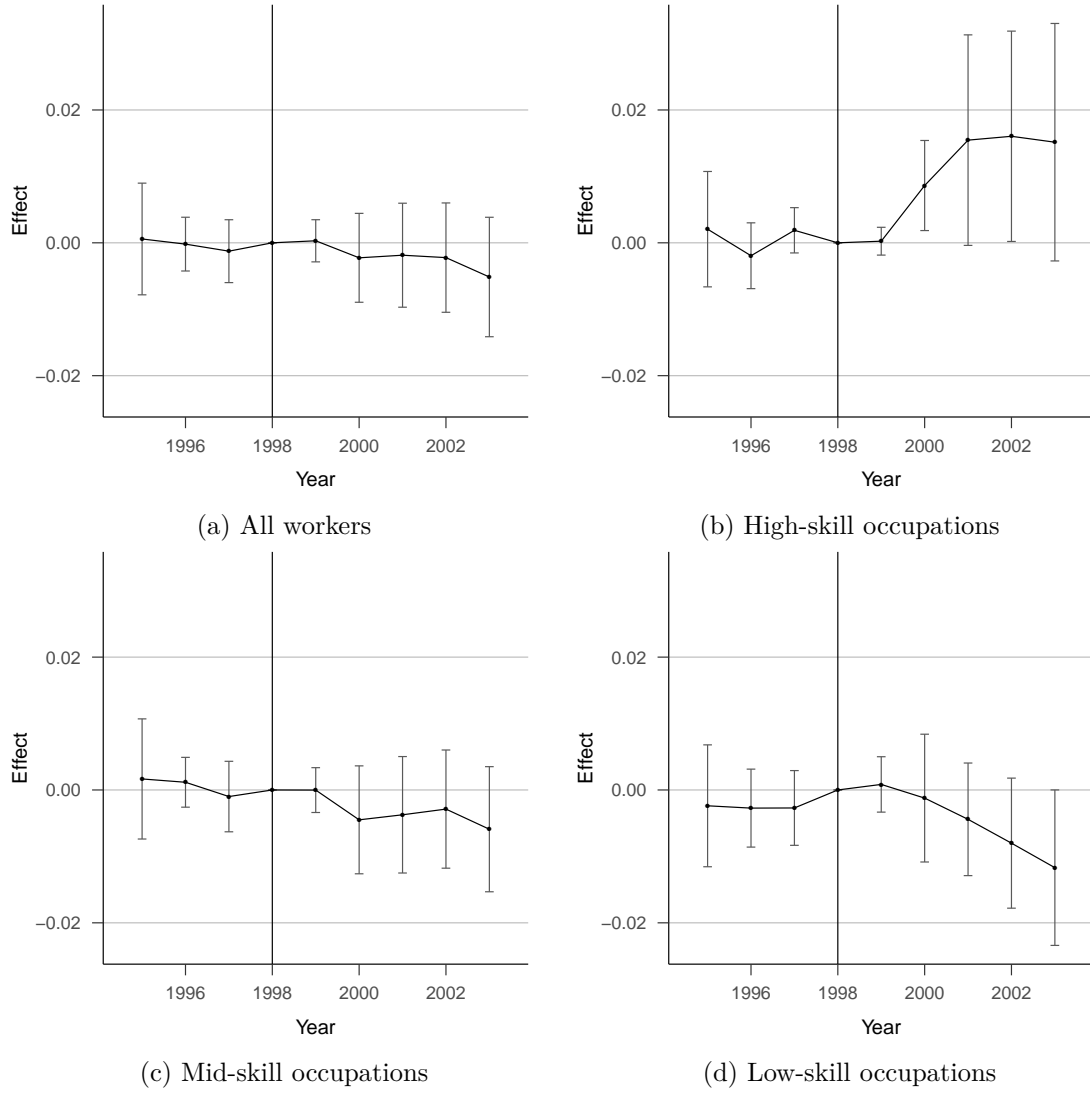
(d) Low-skill occupations

Figure A2: Main effects on hours worked per day

The figure shows annual estimates of the treatment effect in equation (5.1) on hours worked of firm stayers. Regressions are weighted by cell-specific employment in 1998. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See text for details. *Data: DADS.*
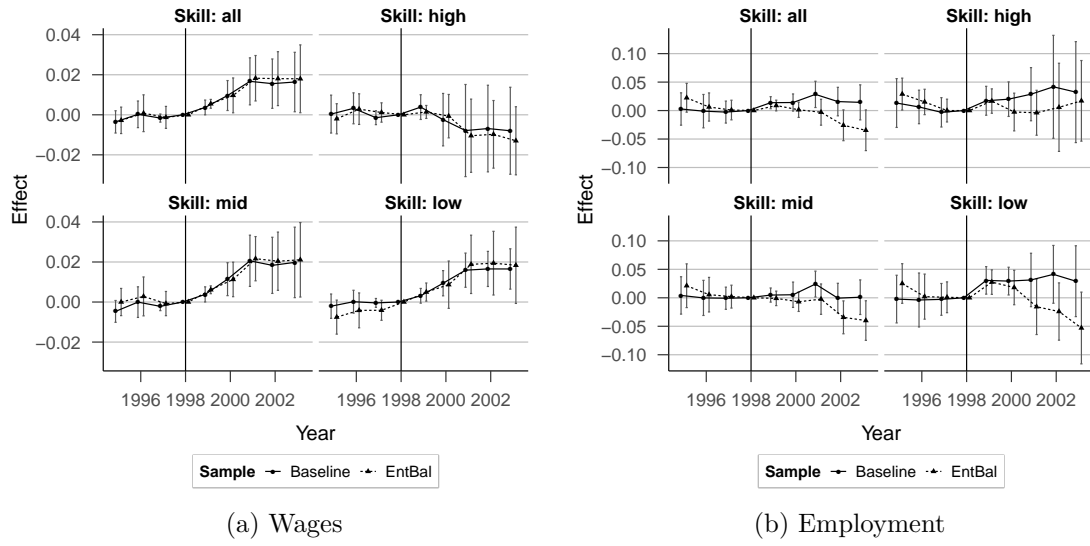
(a) Wages

(b) Employment

Figure A3: Main effects with different matching strategy

The figure shows annual estimates of the treatment effect in equation (5.1) on employment and wages. There are two samples. "Baseline" refers to the main matched sample used in the text, "EntBal" uses Entropy Balancing following Hainmueller (2012). Results from the baseline have a solid line and a dot, results from the entropy balancing have a dashed line and a diamond. Baseline weights units by their skill-specific employment in 1998. Entropy Balancing weights the control units by the entropy weights, and the treated units by unity. Hourly wages are residualized for gender and age. The error bars show the 95% intervals around the point estimate using standard errors clustered at the level of departements. See Section 6.1 for details. *Data: DADS.*

B. Additional tables

Agreement	Change	Effects
Free movement of people	Access to labor markets without restrictions	Expansion of local labor markets
Mutual recognition agreement	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 airlines	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)

Sources: Staatsekretariat für Wirtschaft (SECO) (2008), Eidgenösisches Aussendepartement (EDA) (2016), Hälg (2015).
Note: the treaties on cooperation on research and on agriculture were excluded from the table.

Table B.1: The content of the bilateral treaties between Switzerland and the EU.

C. Data appendix

C.1. Treatment group and matching

C.1.1. Defining the treated labor markets

Labor markets consist of municipalities. Denote the municipalities of labor market i as j_i, $j \in \{1, ... J_i\}$. Define the set of eligible municpialities E. This is the navy blue area in Figure 5a. A labor market i is eligible if $\{j_i\}_{j=1}^{J_i} \cap E \neq \emptyset$, eg, if at least one municipality is in the eligible area. This gives 12 eligible labor markets and denote this set as L_E. Assign to each labor market the distance between the municipality that is furthest away from the next Swiss border crossing, formally $d_i = max_{j \in J_i}\{dist_{j_i, Switz}\}$. Then define $\bar{d} = max_{i \in L_E}\{d_i\}$ and a labor market is in the treatment group if $d_i \leq \bar{d}$. In the present case I have $\bar{d} = 84km$.

C.1.2. Entropy balancing

Entropy balancing calibrates weights for control units in order to achieve overlap in the first and second moments of the covariate distributions between the treated and the control units (Hainmueller, 2012). The method requires setting a balancing constraint m so that the difference of (weighted) means and variances between the treatment and the control group are at most m. I use $m = 0.0001$. Further, I define base weights according to the relative size of each labor market because the baseline estimation also uses the size of the labor market as regression weights. I then match on the following variables: Employment in 1998 and its growth rate since 1995, wage growth from 1995 to 1998, the own-commuting share, employment structure by skill and sector, the education structure of the population, and the employment share of establishments with more than 49 employees. Moreover, because the Paris labor market is an outlier for some of the covariates, the matching algorithm does not converge. I thus drop the labor market of Paris from the pool of potential control units.

Why do the results on employment differ between the baseline matching and the entropy balancing? The results in Figure A3 show that the estimated treatment effects for employment differ between the baseline matching strategy and the entropy balancing, even though the short-run effect on employment of low-skill workers is similar. The most probable explanation for this is that the entropy balancing does not capture some unobserved heterogeneity among the treated labor markets that drives parts of the employment adjustment. In particular, the regression results when using the weights from entropy balancing are not robust to including more covariates, while the main results with the baseline matching strategy are. For instance, controlling for the industry structure at baseline drives the estimated effect on low-skill employment in 2003 from -0.05 to 0. In contrast, controlling for baseline industry structure in the main specification does little to the magnitude and precision of the wage and employment effects, and they also survive the test proposed by Oster (2019).

D. Search model

In this section I describe a simple equilibrium framework with heterogeneous firms and workers based on Bontemps et al. (2000) and Engbom and Moser (2018). I show how wages and the allocation of workers across firms and space adjust when employed workers receive more job offers.

D.1. Workers and firms

French workers live forever and maximize their expected lifetime income. They belong to a skill group $\theta \in \Theta$ and only search within this market. They discount future income at rate ρ and can be employed or unemployed. When unemployed they receive flow utility b_θ and receive new job offers at rate λ_θ^u. When employed they receive wage flow w and receive offers for new jobs at rate λ_θ^e. They are laid off at rate δ_θ. Job offers from French and Swiss firms are drawn randomly from the distribution $F_\theta(w)$ on the support $[\underline{w}_\theta, \overline{w}_\theta]$. Workers know the distribution of job offers and take it as given. Denote the legal minimum wage w_{min}[34].

The value function for an unemployed worker is

$$\rho W_\theta = b_\theta + \lambda_\theta^u \int_{\underline{w}_\theta}^{\overline{w}_\theta} \max\{S_\theta, W_\theta\} dF_\theta(w)$$

and the value function for an employed worker is

$$\rho S_\theta = w + \delta_\theta[W_\theta - S_\theta] + \lambda_\theta^e \int_w^{\overline{w}_\theta} [S_\theta(x) - S_\theta(w)] dF_\theta(x)$$

Unemployed workers follow a reservation wage strategy and accept any job that offers at least ϕ_θ:

$$\phi_\theta = b_\theta + (\kappa_\theta^u - \kappa_\theta^e) \int_{\phi_\theta}^{\overline{w}_\theta} \frac{\overline{F}_\theta(x)}{\beta + 1 + \kappa_\theta^e \overline{F}_\theta(x)} \tag{D.1}$$

where $\kappa_\theta^j = \lambda_\theta^j / \delta_\theta$ for $j = \{u, e\}$, $\beta_\theta = \rho/\delta_\theta$, and $\overline{F}_\theta(x) = 1 - F_\theta(x)$. This implies that there is no wage below ϕ_θ. In a steady-state, flows into unemployment equal flows out of unemployment, and the unemploymyent rate is $u_\theta = \frac{1}{1+\kappa_\theta^u}$. Unemployment is lower when unemployed workers find jobs more quickly.

The model assumes that workers do not search in markets of other skill types, and that job offers from France and Switzerland arrive at the same rate. These strong assumptions are necessary to keep the model tractable. For instance a model where workers receive job offers from two competing regions at different rates would complicate the exposition without giving many more insights. Hoffmann and Shi (2016) analyze a model of this kind and their simulation evidence yields similar predictions as the ones derived here.

To keep the model as simple as possible I also abstract from worker heterogeneity within

---

[34]I abstract from minimum wages at the skill level. If they exist, they lie above the legal minimum wage. Also see the discussion in Section 3.1

segments. Worker heterogeneity is more important to explain unemployment durations (Eckstein and Wolpin, 1990; Bontemps et al., 1999; Eckstein and Van den Berg, 2007) and less crucial for the effect of search frictions on the job on wages.

I further assume that wages are set unilaterally by firms as opposed to wage bargaining: Employer and worker cannot renegotiate wages of an on-going employment spell. The first reason why I make this assumption is that it is much simpler to incorporate search on the job in posting models as opposed to bargaining models (Manning, 2003, p. 996), and on-the-job search is an important feature of the setting I study. The second reason is that the search model nests the competitive model as a special case when the contact rate for employed workers tends to infinity and the highest-productivity firm is the representative firm in the market. I will compare theoretical predictions of the two models below and discuss the empirical evidence in light of the two models.

Firms in France or Switzerland produce with labor from the three worker types that are perfect substitutes:

$$y(p, \{l_\theta\}_{\theta \in \Theta}) = p \sum_\theta l_\theta \tag{D.2}$$

The distribution of firm productivities is $\Gamma(p)$. Having heterogeneous firms helps to interpret the wage differentials across the border documented below: The average Swiss firm is more productive than the average French firm. In reality wages in Switzerland may be higher because of exchange rate differentials but this does not alter the incentives of French firms and workers.

For simplicity I assume that workers of all types are equally productive at the same firm. The assumption implies that wages in the same firm differ across worker types only because search frictions differ. Allowing worker productivity to vary by segment does not change the comparative statics.

Because the production function is linear, the fim maximizes profit flows π_θ for each type separately. As a result, each segment of the labor market is a version of the model of Bontemps et al. (2000) and can be studied in isolation. $K_\theta(p)$ are the (possibly multiple) wages of a firm with productivity p in market θ that maximize profits:

$$K_\theta(p) = \underset{w}{\operatorname{argmax}}\{\pi_\theta(p, w) | \max\{\phi_\theta, w_{min}\} \leq w \leq p\} \tag{D.3}$$

with

$$\pi_\theta(p, w) = (p - w)l_\theta(w).$$

It follows that the lowest firm type in market θ is $\underline{p}_\theta = \max\{\phi_\theta, w_{min}\}$ as any firm below would make losses. Changes in the minimum wage or in the reservation wage may affect the entry threshold for firms.

With on the job search, firms take into account the wages paid at other firms. The decision resolves a trade off between profit per worker and firm size (Burdett and Mortensen, 1998): A higher wage attracts more workers and keeps them longer at the firm but doing so decreases profits per worker. When the productivity distribution is continuous the

productivity rank pins down the pay rank of the firm[35]. Loosely speaking, if two firms pay the same wage but their productivities differ by ϵ, the more productive firm is better off by offering an $\frac{\epsilon}{2}$ higher wage. Total profits increase because it poaches more workers from the other firm which more than offsets the lower profits per workers. It also follows that there is only one optimal wage for each firm type, and that more productive firms pay higher wages and are larger. Firm heterogeneity also implies that more productive firms have more monopsony power: even though on-the-job search induces wage sharing between firms and workers, it is limited at high-productivity firms because they face less competition from other firms.

D.2. Equilibrium effects of an increase in labor market competition

To simplify the comparative statics I make two further assumptions. I assume that the minimum wage is always binding in all segments of the labor market which implies that the productivity threshold for firm entry is fixed. As a result, the labor market integration does not affect entry and exit of firms.

I also assume that the market integration primarily affects the job finding rate of employed workers (κ_θ^e), but not unemployed workers (κ_θ^u). The assumption ensures that the reservation wage remains below the minimum wage.

The data are consistent with the implications of the assumptions. The minimum wage is binding in all segments of the labor market in 1998 in the treatment region. The descriptive analysis in the paper suggests further that the policy primarily affected the job finding rate of employed workers and not of the unemployed.

I also assume a uniform distribution of firm productivities but this is merely to derive closed-form comparative statics.

Proposition 1. *Assume $\phi_\theta < w_{min}$ $\forall \theta$ and $\Gamma(p) \sim U[\underline{p}, \overline{p}]$. Then an increase in the contact rate κ_θ^e*

1. *increases the wages at all firms except the lowest-productivity one. The effect is stronger at more productive firms and weaker in more competitive markets. In perfectly competitive markets the effect tends to 0.*

2. *has an ambiguous effect on firm size. The sign of the effect depends on a unique threshold of firm productivities. More productive firms expand and less productive firms shrink. The treshold is higher in more competitive markets.*

See Appendix D.3 for details and a proof.

Because workers receive more job offers, all firms pay higher wages (except the least productive one) to prevent too many workers from quitting. More productive firms increase wages more because they can attract many more workers than less productive ones. From the workers' point of view, receiving more job offers increases bargaining power which

---

[35]See Bontemps et al. (2000) for a proof. Firms play mixed strategies when they are homogenous (Burdett and Mortensen, 1998).

allows them to extract more rents from their employer. Because rents are higher at more productive firms, wages increase more at those employers. This heterogeneity contrasts with bargaining models where bargaining power is fixed which shuts down the rent-sharing channel of an increase in degree of labor market competition. Moreover, as wages lie closer to the marginal product in more competitive markets, a further increase in the contact rate has a smaller effect on wages.

Because more productive firms increase their wages more, they attract more workers in the new equilibrium. They poach from less productive firms that do not increase wages as much. Because the less productive firms cannot hire more unemployed workers, they become smaller. On aggregate, workers reallocate to more productive firms. In a more competitive market the monopsony power of less productive firms is already low and they have less room to increase wages. In contrast, the most productive firms still enjoy more market power and a further increase in the contact rate makes them increase the wages further, attracting even more workers. In a perfectly competitive market there is no worker mobility because all workers are already at the most productive firm.

Consider two labor market segments that are initially differently competitive. Assuming that there are more productive firms in Switzerland than in France, the reallocation of workers to more productive firms makes more workers flow to Switzerland in the more competitive segment. In the less competitive segment, the threshold for a positive employment effect is lower and so some productive firms in France also become larger. Wages increase more in the less competitive segment[36].

The comparative statics study two steady-states where the contact rate for employed workers varies. The model assumes that wages cannot increase at the current employer and is therefore silent on transitional dynamics between steady-states. One can circumvent this problem by assuming an equal-treatment constraint for firms (Moscarini and Postel-Vinay, 2013): firms have to pay the same wage to all their employees in a given market θ, be it new hires from unemployment, new hires from other firms, or incumbent workers. I will implicitly make the same assumption when studying the effect of the labor market integration on wage growth.

D.3. Derivations

This Section derives the labor market equilibrium from the previous section in detail and largely follows Bontemps et al. (2000). The segmentation by skill type is based on Engbom and Moser (2018).

D.3.1. Worker flows

In any market θ, there are N_θ active firms M_θ active workers of which U_θ are unemployed. Let $G_\theta(w)$ denote the fraction of employed workers in skill group θ that earn at most wage

---

[36]The present search framework also predicts wage gains in Switzerland. The prediction is also present in Hoffmann and Shi (2016): a higher cross-regional job finding rate increases wages in both regions even when the contact rate within region remains constant.

w. In a steady state, the number of workers earning at most wage w does not change over time: there are as many unemployed workers that find jobs paying at most w as there are workers leaving the same jobs because of layoffs or because they find a higher-paying job. Formally we have

$$\lambda_\theta^u U_\theta F_\theta(w) = [\delta_\theta + \lambda_\theta^e \overline{F}_\theta(w)](M_\theta - U_\theta) G_\theta(w) \tag{D.4}$$

Solving this equation at $w = \overline{w}_\theta$ gives the unemployment rate $u_\theta = \frac{1}{1+\kappa_\theta^u}$. With this result, one can also show that the observed wage distribution relates to the offer distribution as follows: $G_\theta(w) = \frac{F_\theta(w)}{1+\kappa_\theta^e \overline{F}_\theta(w)}$. The more quickly workers climb the job ladder, the more employment is concentrated among higher-paying firms.

D.3.2. Firms

Since workers meet firms at random, the average firm size for firms paying wages in the interval $[w, w + \epsilon]$, where $\epsilon \to 0$ is

$$l_\theta(w) = \frac{M_\theta - U_\theta}{N_\theta} \frac{dG_\theta(w)}{dF_\theta(w)} = \frac{M_\theta - U_\theta}{N_\theta} \frac{1 + \kappa_\theta^e}{[1 + \kappa_\theta^e \overline{F}_\theta(w)]^2} \tag{D.5}$$

where $\frac{dG_\theta(w)}{dw}$ was taken from the relation above. As in the model with homogenous firms, high-wage employers are larger because they can attract more workers and fear less poaching from other firms.

Firms maximize profit flows $\pi_\theta(p, w) = (p - w)l_\theta(w)$. $\underline{p}_\theta$ is the productivity threshold for active firms and profits are negative for any $p < \underline{p}_\theta$. Denote the distribution of active firms by $\Gamma_\theta(p)$ which is the probability of being a firm of at most productivity p conditional on being active in the market:

$$\Gamma_\theta(p) = \frac{\Gamma_0(p) - \Gamma_0(\underline{p}_\theta)}{\overline{\Gamma_0}(\underline{p}_\theta)} \tag{D.6}$$

The number of active firms is therefore $N_\theta = N_0 \overline{\Gamma_0}(\underline{p}_\theta)$, eg the number of all possibly active firms multiplied by the fraction of firms above the threshold productivity.

The optimal strategy of a firm with productivity p maximizes profits subject to the wage constraint:

$$K_\theta(p) = \underset{w}{\operatorname{argmax}}\{\pi_\theta(p, w) | \max\{\phi_\theta, w_{min}\} \le w \le p\} \tag{D.7}$$

where

$$\pi_\theta(p, w_\theta) = (1 + \kappa_\theta^e)\frac{M_\theta - U_\theta}{N_0 \overline{\Gamma_0}(\underline{p})} \frac{p - w}{[1 + \kappa_\theta^e \overline{F}_\theta(w)]^2} \tag{D.8}$$

follows from equations (D.5) and (D.6). For future reference, define $A_\theta \equiv (1 + \kappa_\theta^e)\frac{M_\theta - U_\theta}{N_0 \overline{\Gamma_0}(\underline{p}_\theta)}$ and therefore $\pi_\theta(p, w_\theta) = A_\theta \frac{p - w_\theta}{[1 + \kappa_\theta^e \overline{F}_\theta(w_\theta)]^2}$.

Because firms are indifferent between all strategies that solve (D.7), define $F_\theta(.; p)$ as the probability distribution of firm type p over all optimal strategies. Thus the overall

wage distribution in the economy is $F_\theta(.) = \int F_\theta(.;p)d\Gamma_\theta(p)$

D.3.3. Market equilibrium

An equilibrium is a set $(\phi_\theta, \underline{p}_\theta, \{F_\theta(.;p), p > \underline{p}_\theta\})$ such that

1. The distribution of wage offers is $F_\theta(.) = \int F_\theta(.;p)d\Gamma_\theta(p)$.

2. Only firms with at least productivity $\underline{p}_\theta$ are active and their distribution is given by (D.6).

3. ϕ_θ satisfies (D.1).

4. $F_\theta(.,p)$ is a distribution over all strategies that satisfy (D.7).

Bontemps et al. (2000, Proposition 3) show that there exists a wage function $K_\theta(p)$ such that the wage distribution reflects the productivity distribution, if this distribution is continuous. Firms play pure strategies because only one strategy is optimal for a given type. As a result, firms with higher productivity pay higher wages, the wage distribution is continuous and $\underline{w}_\theta = \max\{\phi_\theta, w_{min}\}$.

The first-order condition of a firm of type p is $\frac{\partial \pi_\theta(p, w_\theta)}{\partial w_\theta} = 0 \Leftrightarrow -l_\theta(w) + (p-w)l'_\theta(w) = 0$ which results in

$$- [1 + \kappa_\theta^e \overline{F}_\theta(w)] + 2\kappa_\theta^e f_\theta(w)(p-w) = 0 \tag{D.9}$$

Firms with the lowest productivity pay the lowest wages: $K(\underline{p}_\theta) = \underline{w}_\theta$.

Consider the marginal increase of profits for a marginal increase in productivity, $\frac{\partial \pi_\theta[K_\theta(p)]}{\partial p}$:

$$\frac{\partial}{\partial p}[p - K_\theta(p)]l_\theta[K_\theta(p)] = \overbrace{l_\theta[K_\theta(p)]}^{\text{output incumbents}} - \overbrace{l_\theta[K_\theta(p)]K'_\theta(p)}^{\text{wage incumbents}} + \overbrace{pl'_\theta[K_\theta(p)]K'_\theta(p)}^{\text{output new hires}} - \overbrace{K_\theta(p)l'_\theta[K_\theta(p)]K'_\theta(p)}^{\text{wage new hires}} \tag{D.10}$$

which simplifies to

$$\pi'_\theta(p) = l_\theta[K_\theta(p)] \tag{D.11}$$

This follows because when a firm increases productivity, its wage increases. The optimal wage equalizes marginal labor cost with marginal profits. Labor cost increase because of higher wages for incumbent workers and because of new hires that are attracted by the higher wage. The new hires increase output further. The three last terms exactly offset each other, and the marginal profit is just the marginal increase in output from the incumbent workers.

The marginal profit in (D.11) is a differential equation with initial condition $\pi_\theta(\underline{p}) = (\underline{p}_\theta - \underline{w}_\theta)l_\theta(\underline{w}_\theta)$. Therefore

$$\pi_\theta(p) = (\underline{p}_\theta - \underline{w}_\theta)l_\theta(\underline{w}_\theta) + \int_{\underline{p}}^{p} l_\theta[K_\theta(x)]dx \tag{D.12}$$

and since $\overline{F}_\theta[K_\theta(x)] = \overline{\Gamma}_\theta(x)$, we have $l_\theta[K_\theta(x)] = \frac{A_\theta}{[1+\kappa_\theta^e \overline{\Gamma}_\theta(x)]^2}$, and using $\underline{p}_\theta = \underline{w}_\theta$:

$$\pi_\theta(p) = A_\theta \int_{\underline{w}_\theta}^p \frac{1}{[1 + \kappa_\theta^e \overline{\Gamma}_\theta(x)]^2} dx \tag{D.13}$$

Using $\pi_\theta(p) = [p - K_\theta(p)]l_\theta[K_\theta(p)]$, rearrange for $K_\theta(p)$, substitute (D.13) for profits and (D.5) for the firm size and use $F_\theta(x) = \Gamma_\theta(x)$ gives the wage as a function of the distribution of productivity, the contact rate, firms' productivity and the reservation wage:

$$K_\theta(p) = p - [1 + \kappa_\theta^e \overline{\Gamma}_\theta(p)]^2 \int_{\underline{w}_\theta}^p \frac{1}{[1 + \kappa_\theta^e \overline{\Gamma}_\theta(x)]^2} dx \tag{D.14}$$

The number of equilibria depends on the parameters of the model. The equilibrium exists for $\overline{p} < \infty$ (see Bontemps et al. (2000) for details). The interdependence of the reservation wage ϕ_θ and the threshold productivity $\underline{p}_\theta$ make the model non-recursive.

D.3.4. Equilibrium with uniform productivity and proof of proposition

Assume now that firm productivity is distributed uniformly on the interval $[\underline{p}, \overline{p}]$. The assumption allows me to derive closed-form solutions for the equilibrium wage function and assess comparative statics. Also assume that the minimum wage is binding in all markets: $\phi_\theta < w_{min} \ \forall \theta$ and $\underline{p}_\theta \equiv \underline{p} \ \forall \theta$. The assumptions imply that the entry threshold does not change when the contact rate for employed worker changes. Since the entry threshold is constant across markets, we also have $N_\theta \equiv N \ \forall \theta$.

The wage offered by a firm with productivity p is then

$$K_\theta(p) = p - \frac{(\overline{p} - p)(p - \underline{p}) + \kappa_\theta^e(\overline{p} - p)(p - \underline{p})}{(1 + \kappa_\theta^e)(\overline{p} - \underline{p})} \tag{D.15}$$

I first show that a reduction in the search friction on the job (an increase in the contact rate for employed workers) workers increases the wages at all firms except the with the lowest productivity.

$$\frac{\partial K(p)}{\partial \kappa_\theta^e} = -\frac{(\overline{p} - p)(p - \underline{p})(1 + \kappa_\theta^e)(\overline{p} - \underline{p}) - \left[(\overline{p} - p)(p - \underline{p}) + \kappa_\theta^e(\overline{p} - p)(p - \underline{p})\right](\overline{p} - \underline{p})}{(1 + \kappa_\theta^e)^2(\overline{p} - \underline{p})^2} \tag{D.16}$$

Simplifying and collecting terms yields

$$\frac{\partial K(p)}{\partial \kappa_\theta^e} = \frac{(p - \underline{p})^2}{(1 + \kappa_\theta^e)^2(\overline{p} - \underline{p})} \geq 0 \tag{D.17}$$

As the numerator is increasing in p and the denominator is increasing in κ_θ^e, we have $\frac{\partial^2 K(p)}{\partial \kappa_\theta^e \partial p} > 0$ and $\frac{\partial^2 K(p)}{\partial \kappa_\theta^e \partial \kappa_\theta^e} \leq 0$, and $\lim_{\kappa_\theta^e \to \infty}(\frac{\partial}{\partial \kappa_\theta^e} K(p)) = 0$. ∎

Now consider how the employment of a firm with productivity p responds to a reduction

in search frictions on the job.

$$\frac{\partial l_\theta[K_\theta(p)]}{\partial \kappa_\theta^e} = \frac{M_\theta - U_\theta}{N} \frac{[1 + \kappa_\theta^e \overline{\Gamma}(p)]^2 - 2(1 + \kappa_\theta^e)[1 + \kappa_\theta^e \overline{\Gamma}(p)]\overline{\Gamma}(p)}{[1 + \kappa_\theta^e \overline{\Gamma}(p)]^4} \tag{D.18}$$

Simplifying yields

$$\frac{\partial l_\theta[K_\theta(p)]}{\partial \kappa_\theta^e} = \frac{M_\theta - U_\theta}{N} \frac{1 - \overline{\Gamma}(p)(2 + \kappa_\theta)}{[1 + \kappa_\theta^e \overline{\Gamma}(p)]^3} \tag{D.19}$$

The sign of the effect only depends on $1 - \overline{\Gamma}(p)(2 + \kappa_\theta)$, and all the remaining terms are positive. Because $\overline{\Gamma}(p)$ is monotonically decreasing in p, there exists a unique threshold $\underline{\tau}_\theta^l$ above which the term is positive:

$$\frac{\partial l_\theta[K_\theta(p)]}{\partial \kappa_\theta^e} \Leftrightarrow p > \overline{p} - \frac{\overline{p} - \underline{p}}{(2 + \kappa_\theta^e)} \equiv \underline{\tau}_\theta^l.$$

The threshold $\underline{\tau}_\theta^l$ is increasing κ_θ^e. ∎

E. Alternative model where the supply elasticity to individual firms is endogenous

This exposition follows Kaplow and Shapiro (2007) and contemporaneous work by Arnold (2019). Denote the local market by j. Assume there is a single dominant firm that employs $L(w_j)$ workers where w_j is the wage set by the firm. There is a fringe of small firms that are price-takers and they employ $R(w_j)$ workers. Total employment in the local market is $M(w_j)$ with $\frac{\partial M(w_j)}{\partial w_j} > 0$. Employment of the dominant firm is then $L(w_j) = M(w_j) - R(w_j)$. Taking derivatives with respect to w_j gives

$$\frac{\partial L(w_j)}{\partial w_j} = \frac{\partial M(w_j)}{\partial w_j} - \frac{\partial R(w_j)}{\partial w_j} \tag{E.1}$$

Multiply by $\frac{w_j}{L}$ and expand the right-hand side as follows

$$\frac{\partial L(w_j)}{\partial w_j} \frac{w_j}{L} = \frac{\partial M(w_j)}{\partial w_j} \frac{w_j}{L} \frac{M(w_j)}{M(w_j)} - \frac{\partial R(w_j)}{\partial w_j} \frac{w_j}{L} \frac{R(w_j)}{R(w_j)} \tag{E.2}$$

Denote the market share of the large firm by $s_j \equiv \frac{L(w_j)}{M(w_j)}$ and the residual share by $1 - s_j \equiv \frac{R(w_j)}{M(w_j)}$. Denote further $\varepsilon_{market} = \frac{\partial M(w_j)}{\partial w_j} \frac{w_j}{M(w_j)}$ the local labor supply elasticity and $\eta_R = \frac{\partial R(w_j)}{\partial w_j} \frac{w_j}{R(w_j)}$ the labor demand elasticity of the fringe firms. The elasticity to the large firm is then

$$\frac{\partial L(w_j)}{\partial w_j} \frac{w_j}{L} = \varepsilon_j = \frac{\varepsilon_{market} - \eta_R(1 - s_j)}{s_j} \tag{E.3}$$

In the limiting cases where the firm is a monopsonist ($s_j = 1$), the elasticity of labor supply to the firm equals the elasticity to the market. In a perfectly competitive market

the market share of each firm is infinitesimally small and it faces an infinitely elastic labor supply. Assuming that the labor demand elasticity of the fringe firms is negative, a smaller market share of the large firms makes supply to that firm more elastic:

$$\frac{\partial \varepsilon_j}{\partial s_j} = \frac{\eta_R - [\varepsilon_{market} - \eta_R(1 - s_j)]}{(s_j)^2} < 0 \tag{E.4}$$

The labor market integration can be thought of as reducing the market share of the largest firm in the market as it now faces more competitors from across the border. Moreover as low-skill workers are less mobile, their relevant market is smaller which implies a larger share for the large firm, rendering the supply curve to that firm less elastic. This is one reason for higher monopsony power in the low-skill labor market.