Universität St.Gallen

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February 2019 Discussion Paper no. 2019-03

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University of St.Gallen

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Publisher:	School of Economics and Political Science Department of Economics University of St.Gallen Müller-Friedberg-Strasse 6/8 CH-9000 St.Gallen Phone +41 71 224 23 07
Electronic Publication:	http://www.seps.unisg.ch

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[1] I would like to thank Mirjam Bächli, Michael Lechner, Anthony Strittmatter, Teodora Tsankova, the participants to the SEW research seminar on 4-6 June 2018, the participants to the SEW research seminar on 22 October 2018, the participants to the research seminar at the University of Geneva on 8th February 2019, the participants to the YSEM conference in Zurich on 14-15 February 2019, and the participants to the brown bag seminar in St.Gallen on 20th Febraury 2019 for their rich and insightful advice.

Abstract

We analyse the impact of an inflow of foreign workers on positional wage mobility in a small open economy like Switzerland. We exploit the quasi-natural experiment constituted by the entry into force of the Agreement on the Free Movement of Persons between Switzerland and the EU on 1st June 2002. We compute conditional average treatment effects with machine learning methods, and we find evidence of relevant heterogeneity in the impact of this policy on wage mobility.

Keywords

Wage mobility, Bilateral Agreements, causal forest, Conditional Average Treatment Effect

JEL Classification

C14, J31

1 Introduction

The aim of this paper is to assess the short-term impact of an opening of the labor market to an inflow of foreign workers on relative or positional wage mobility of natives. With respect to the previous literature, we will focus on estimation of the impact across the whole income distribution, instead than only considering mean estimations. Further, the focus of the present work lies in assessing the impact of a policy change on the dynamics of wages, i.e. on individual wage mobility patterns, instead than on wage levels alone.

We build on existing research by exploiting information from a quasi-natural experiment. The framework of the quasi-natural experiment is provided by the entry into force of the Bilateral Agreements I between Switzerland and the European Union, which took place on 1st June 2002, and in particular the Agreement on the Free Movement of persons. This first round of agreements included several measures which were applied at a national level, thus lifting previous restriction on EU citizens wanting to come to work in Switzerland. They also included one policy change which was implemented on a regional level, i.e. the introduction of a broader definition of cross-border workers. Before 2002, indeed, only people living within a radius of 20 km from the Swiss border were allowed to enter the Swiss labor market as cross-border workers and their job permit was only valid for a single Canton (cross border workers had neither geographical nor professional mobility). On the contrary, after 2002 people coming from every part of the neighbouring countries could qualify as cross-border workers, and they became able to move within the whole Swiss border region, but not outside it (they enjoyed limited geographical mobility). The Swiss border region is represented in Figure 3 in the Appendix.

In the first years after the Bilateral Agreements came into force (2002), this liberalization was mitigated by the priority requirement. This means that, before hiring a foreign cross-border worker, firms had to show to the cantonal migration office that they had not been able to find a worker with the desired characteristics within a reasonable time frame. This requirement was abandoned in 2004, and the concept of Swiss border region itself was then abolished in 2007. As a consequence of the above-mentioned liberalization of the definition of the definition of cross-border workers, their number in the Swiss border region increased relevantly between 1998 and 2010, going from 7% to 9.5% of total employment (Beerli, Ruffner, Siegenthaler and Peri (2018), see also Figure 4 in the Appendix). The entry into force of the agreement on the free movement of persons provides the adequate framework for an impact evaluation study. Indeed, starting from 2002, the Swiss municipalities were exposed to inflows of foreign workers of different intensities, depending on their distance from the national border. Municipalities in the border region were contemporaneously exposed to both flows of cross-border workers and to flows of foreigners coming to work and live in Switzerland (see Figures 4-5 in the Appendix). Hence, in this study we will consider a continous treatment, i.e. the distance of each municipality from the national border, expressed by the commuting driving time.

The aim of the present work is to assess whether this opening of the labour market significantly changed the degree of individual wage mobility, i.e. the chances of moving up or down in the wage distribution from one year to the following one. More specifically, we are interested in determining which groups (defined by their age, gender, education level, sector of employment and other individual characteristics) have benefited or on the contrary have been penalized by the new inflows of foreign workers. Note that this research question extends the previous research, since we do not consider here "benefit" and "penalization" simply in terms of wage or employment probabilities. Instead, we define "benefit" as, for example, an increase in wage mobility for those workers currently being in a low position in the wage distribution and "penalization" as a decrease in wage mobility for the same group.

The contribution of the present paper is twofold. As mentioned above, this is the first study on the impact of an increase in labor market openness on wage mobility. The existing literature almost exclusively focused on the effect of migration on employment and wage levels. Second, we apply machine learning methods, and in particular causal forests, in order to compute conditional average treatment effects (CATEs) for workers with different individual characteristics, thus introducing a methodology that is essentially new in the field of wage dynamics studies. Beerli, Ruffner, Siegenthaler and Peri (2018) focused on mean impact estimations (on wages and hours worked). However, we find evidence of relevant impact heterogeneity across different groups of workers. To the best of our knowledge, there are only other two studies which apply causal forests algorithms to labor market topics: Bertrand et al. (2017), who analyze the heterogeneous impact of an occupational program in Cote d'Ivoire on wages and employment, and Davis and Heller (2017), who put under scrutiny heterogeneity of the impact of two summer jobs programs in the US.

Finally, as far as the relevance of our dependent variable is concerned, wage mobility is a distinctive feature of an economy, since it determines the trend of long-term income inequality (Bonhomme and Robin (2009), Arellano and Bonhomme (2017)). The theme of wage mobility and earnings dynamics (both intergenerational and intragenerational) currently occupies a relevant position in the academic debate (e.g. Lefgren et al. (2012), Corak (2013), Chetty et al. (2014), Nybom and Stuhler (2016)). The interest in wage mobility as a relevant economic variable is further motivated by the rising trend of long-term income inequality in most developed economies in the latest decades (Picketty and Saez (2003), Autor et al. (2006), Goos et al. (2009), Atkinson et al. (2011), Bonke et al. (2014), Gabaix et al. (2016)).

As far as the external validity of the estimated causal effects is concerned, according to Beerli, Ruffner, Siegenthaler and Peri (2018), this change in policy was permanent (and perceived as such), in contrast with other cases of changes in the migration policy which were only temporary. We deem that our estimation results would provide useful policy insights if a similar regional policy were to be replicated elsewhere. For example, one may think of the United States introducing a similar enlargement of the commuting policy for Mexican workers. The remaining of this paper is organized as follows. Section 2 presents the methods used for estimation, whereas Section 3 is devoted to the description of the dataset. In Section 4 the estimation results are presented and discussed. Section 5 concludes.

1.1 Literature review

There is a broad existing literature on the influence of immigration on wage and employment probabilities of natives (among the most recent see e.g. Card (2001), Borjas (2003), Gerfin and Kaiser (2010), Aydemir and Borjas (2011), Glitz (2012), Peri (2012), Smith (2012), Cadena (2013), Patel and Vella (2013), Abramitzky et al. (2014), Olney (2015), Peri (2016), Dustmann et al. (2016 and 2017)). However, until now little attention has been devoted to the impact of workers' migration on the degree of wage mobility in the labor market. Indeed, most of the previous research focused on the extent of competition between immigrant and native workers in the labor market (e.g. Cattaneo et al. 2015), and on the estimation of the potential wage penalty faced by immigrants following their arrival. McHenry (2015) analyzes instead the impact of immigration on the stock of human capital of natives and Buchinsky et al. (2014) focus on labor market outcomes of immigrants, whereas Bijwaard et al. (2014) analyze the interaction between unemployment and return probability of immigrant workers. However, there is still room for investigation on impact of inflows of foreign workers on individual wage mobility.

There is a long-standing debate over the impact of immigrant workers inflows on the labor market outcomes of natives, and results have often been contradictory (Blau and Kahn (2015)). Indeed, Borjas (2003) and Borjas et al. (2008) have found a large negative impact of migration on natives' wages, whereas Card (2009) and Ottaviano and Peri (2012) have found a small and often positive impact of migration on the same variable. However, wage mobility has not been included among the outcomes until now. Most of the above-mentioned studies consider aggregates such as cities of regions. Cattaneo et al. (2015) is one of the first papers in this field to focus on individual labor market outcomes. The authors find evidence of a positive impact of migration on both wages and professional upward mobility of natives, and no impact on their probability of being unemployed in the following three years. Similar findings are presented by Foged and Peri (2016) with reference to the impact of a refugee dispersal policy which was in place in Denmark between 1986 and 1998. Card and DiNardo (2000) find evidence that, contrary to the common belief that immigrant inflows can cause outflows of native workers, increases in immigrant population in certain skill groups leads to a small increase in the native population in the same skill-group, i.e. there is no crowding-out.

On the other hand, from a macroeconomic perspective, Ortega and Peri (2014) find a positive and statistically significant relationship between openness to immigration of a country and long-run income per capita of its inhabitants. Kerr and Lincoln (2010) find evidence of a positive influence of the inflow of high-skilled migrants, following the changes in the H-1B visa program in the US, on innovation in the fields of science and engineering. Similarly, Peri (2012) finds no evidence of a crowding-out of native employment due to migration and, on the contrary, argues that migration is positively associated with growth in total factor productivity and income per worker. Peri et al. (2015) claim that foreign-born and native computer workers are complement rather than substitute inputs. As far as highly-educated workers are concerned, Peri and Sparber (2011) find that foreign-born and native graduates are imperfect substitutes, in the sense that the former usually specialize in jobs requiring analytic and computation skills, whereas the latter specialize in jobs requiring interactions and communication. In their meta-analytical study, Longhi et al. (2005) find indeed that results on the impact of migration on labor market outcomes notably vary depending on the country considered and on the type of modelling approach. However, to the best of our knowledge, the impact of migration flows on earnings dynamics, and not only earnings levels, has not been put under scrutiny until now. Kim (2013) analyzes the influence of being foreign-born on the probabilities of experiencing upward or downward wage mobility. However, he does not investigate the effect of an increase in the number of immigrant workers on the degree of wage mobility experienced by natives. Hence, we do not have a clear-cut theoretical expectation on the sign or the size of this impact.

There are currently very few studies that exploit a quasi-experimental framework in order to assess the impact of immigration on relevant labor market variables. Among the rare examples there are the Mariel boat-lift analyzed by Card (1990) and the migration flows caused by the Hurricane Mitch (Kugler and Yuksel (2008)). Another relevant example is the study of the impact of the liberalization of migration between East and West Germany following the fall of the Berlin Wall, carried out by Glitz (2012). The author finds evidence of a detrimental effect of migration flows on employment probabilities of natives, but not on their wages.

The empirical strategy of the present paper is in some regards similar to that used by Dustmann et al. (2017). The authors, indeed, exploit a commuting policy that allowed an unexpected increase in the number of Czech workers into the German border area, and find that this large migration inflow caused a sharp decline in native employment and a small decline in native wages. These effects, however, are subject to non-negligible heterogeneity across age groups.

Dustmann et al. (2012) claim that it is important to estimate the impact of immigration on the whole distribution of natives' wages, as compared to previous studies which were limited to mean-estimation of the impact, and find evidence of a depression of wages due to immigration below the lowest 20th percent of the distribution, whereas the effect is positive in the upper part of the wage distribution. This finding emphasizes the necessity of a flexible modelization, in order to take into account potential heterogeneity of the treatment effect across the wage distribution. For this reason, we will compute conditional average treatment effects via machine learning methods, in the spirit of Wager and Athey (2018), to assess the impact of the free movement policy on workers being in different parts of the wage distribution and with different individual characteristics.

2 Identification strategy

2.1 The conditional independence assumption

We apply the potential outcome framework, in the spirit of Roy (1951) and Rubin (1974), in order to estimate the impact of an opening of the labor market on the degree of wage mobility for different groups of native workers. We exploit the fact that Swiss municipalities were differently affected by the inflow of foreign workers, depending on their distance from the national border. Furthr, as mentioned above, the liberalization in the definition of cross-border workers only affected municipalities in the Swiss border region (until it was abolished in 2007). It is worth noting that the definition of the Swiss border region took place via the stipulation of bilateral treaties between Switzerland and the neighbouring countries. In particular, Bilateral agreements were signed with Italy in 1928, with France in 1946, with Germany in 1970 and with Austria in 1973. The definition of border regions does not necessarily correspond to the geographical features of the territory (see Figure 3 in the Appendix). Further, the Agreement on the free movement of persons was negotiated by the federal government, not by the Cantons, and hence the local economic conditions of border and non-border municipalities were ignored in the process (Beerli, Ruffner, Siegenthaler and Peri (2018)). Hence, it seems reasonable to suppose that the conditional independence assumption holds, as we will state in the following.

Of course, the above-mentioned liberalization also allowed Swiss individuals to go working in the border area of the neighbouring countries. However, we will not consider this effect because, as explained by Beerli, Ruffner, Siegenthaler and Peri (2018), the rate of employment of Swiss individuals in the border regions of Italy, France and Germany did not significantly change in the years following the Bilateral Agreements I. Indeed, the wage differential was always strongly in favor of the Swiss side of the border. In this framework, we will consider a continuous treatment, i.e. the distance of each municipality from the Swiss national border, measured via driving commuting time, in the period from 2002 onwards.

It is worth considering that the conditional independence assumption (i.e. the assumption that assignment to the treatment is independent from the potential outcome, conditional on the observable characteristics) may fail if workers are able to relocate freely from the border region to the non border region and vice versa. Let us say, for example, that those with the lowest levels of wage mobility, may decide to move from a border municipality to another one outside the border area, because they are dissatisfied with the labor market conditions in the border region (i.e. because they are stuck in the low-wage trap). However, we argue that the decision of moving usually requires a certain amount of time, since it entails relevant monetary and non-monetary costs. Therefore, we are confident that in the period considered here (2002-2005) this potential effect should not lead to a relevant bias in our estimation results. Moreover, the decision of moving is likely to be highly dependent on the worker's characteristics, such as age, gender or educational level, and we control for all these variables. Hence, we expect conditional independence to be preserved. Past research (e.g. Card and DiNardo (2000), Peri and Sparber (2011)) has not found significant outflows of natives in response to immigration. Further, on the same dataset that we will describe in Section 3, Beerli, Ruffner, Siegenthaler and Peri (2018) estimate the impact of the free movement policy on both inflows and outflows of local employment by natives. Their estimated coefficients are hardly ever statistically significant, thus suggesting that the reaction of native workers to the regional policy change by moving in a different municipality or in a different Canton was quantitatively limited.

2.2 Definitions of wage mobility

The outcome variable, y_{it}, is a measure of wage mobility. In this paper we use two alternative measures of wage mobility. The first one refers to the concept of absolute wage mobility and is equal to the percentage change in individual annual wage from one year to the following one (excluded bonuses and other forms of windfall earnings):

$$y_{it}^{abs} = logwage_{it} - logwage_{i,t-1} \tag{1}$$

The second definition refers instead to the concept of relative or positional wage mobility, and it is defined as the change in the individual income percentile (q_{it}) from one year to the following one:

$$y_{it}^{rel} = q_{it} - q_{i,t-1}. \tag{2}$$

2.3 Causal forest

To tackle the issue of heterogeneity in treatment effects, in the present paper we will compute CATEs via the causal forest algorithm developed by Wager and Athey (2018) and implemented by the authors in the R package "grf" (generalized random forest), which is publicly available at CRAN. As explained by Wager and Athey (2018), the advantage of using a causal forest instead of a single causal tree is that it is often not straightforward to select the best tree. They further argue that is generally better to generate many acceptable trees and then average their predictions, rather than seeking a single highly-optimized tree.

In the present paper, the use of machine learning methods is motivated by the willingness to analyze heterogeneity of treatment effects across different types of workers. We believe, indeed, that the influence of an opening of the labor market to flows of foreigners on wage mobility (both absolute and relative) can be dramatically different for workers with different individual characteristics (e.g. being in different parts of the wage distribution, or having completed different educational levels). In the study of heterogeneity in treatment effects, the interest traditionally lies in estimating the coefficient of the interaction between treatment and a dummy variable identifying a group, in the framework of a linear specification. However, looking at subgroups defined in this way is rather limiting and arbitrarily searching for such subgroups may lead to spurious conclusions. A different approach consists in considering the identification of heterogeneous treatment effects as a prediction problem (Kleinberg et al. (2015), Mullainathan and Spiess (2017)), which is what we plan of doing here.

In supervised machine learning methods such as regression trees or random forests, a model of the relationship between a set of covariates, X, and an observed outcome, Y, is first built by training the model on a dataset where (Y, X) are both observed. In a second step, that model is used to predict the outcome on a population for which only the characteristics X are observed. This approach can be applied to the prediction of treatment effects.

We rely here on the algorithm for causal trees developed by Athey and Imbens (2016) and extended by Wager and Athey (2018). Athey and Imbens (2016) adapt classification and regression trees (CART) to the specific case of predicting treatment effects conditional on a set of control variables. Causal trees differ from CART in two main aspects. First, the splitting criterion has been adapted in order to maximize the variation in treatment effects across leaves, instead than the variance of the outcome. Second, an independent sample, different from the sample used to partition the data, is used to estimate treatment effects within each leaves (this property is called "honesty" by Athey and Imbens (2016)), which should alleviate the risk of overfitting. This additional sample splitting also makes inference on treatment effects valid, conditional on a tree. As mentioned above, this framework has been recently extended by Wager and Athey (2018) to random forests based on causal trees and to the possibility of making causal inference with the estimation results. The work by Wager and Athey (2018) is the basis for our causal forest estimations which will be presented in Section 4.

As explained above, we aim at estimating the conditional average treatment effect (CATE):

$$\tau(x) = E[Y_i(1) - Y_i(0)|X_i^K = x], \tag{3}$$

where X^K is a vector of K baseline covariates and Y is the outcome of interest. This requires a dataset $(Y_i^{obs}, W_i, X_i^K), i = 1, ..., N$, considered as an i.i.d. sample drawn from an infinite population, where W stands for the treatment (which is continous in our case) and Y^{obs} is the realized observed outcome. As usual, we need to make the assumption of unconfoundedness, i.e. that treatment is randomized conditional on observable characteristics, which is reasonable in our context, as explained in Section 2.1.

To be more precise, we rely here on the classical set of unconfoundedness assumptions, as reported by, for example, Imbens (2000) and Lechner (2001). Our assumptions are:

1. the conditional indipendence assumption, i.e. there are no features other than those already included in the vector of explanatory variables that jointly influence treatment assignment and potential outcome,

2. the common support assumption, i.e. there is sufficient overlap between the values of the covariates in the control group and in the treatment group,

3. the stable-unit-treatment-value assumption (SUTVA), which implies that the observed value of the treatment does not depend on the treatment allocation of other population members, i.e. potential spillover and treatment size effects are ruled out[1],

[1]One potential concern is that the liberalization of the Swiss labor market to the inflow of foreigners caused wage dumping and hence had general equilibrium effects. If this were true, than the SUTVA would fail. However, there are two main reasons why we believe that our assumption is reasonable. First, as it has been shown by Beerli, Ruffner, Siegenthaler and Peri (2018), the immigrants were for the most part highly-skilled, hence it is unlikely

4. and finally the exogeneity assumption, which implies that the observed values of the confounders do not depend on the treatment status.

In the estimation of the causal forest, as a first step, our data is split in two separate samples: a training sample which is used to build the model, and a test sample. All subsequent analysis will be performed on this latter test sample, which is not involved in any step of the construction of the prediction model. This does not represent a serious limitation in our model, since we have relatively small K compared to N. Then, the model giving a prediction of CATE is built using a training sample set to 50% of the full sample (N). In a following step, the CATE is estimated on the test sample (set to 50% of N). Our X^K, as mentioned above, is a set of covariates including individual and workplace characteristics, such as education or size of the firm (see Table 14 in the Appendix for the full list of covariates). Given a causal tree with leaves $L(x)$, suppose that the leaves are small enough that the (Y_i, W_i) pairs corresponding to the indices i for which $i \in L(x)$ act as though they had come from a randomized experiment. Then, as explained by Wager and Athey (2018), it is natural to estimate the treatment effect of any $x \in L$ as follows:

$$\hat{\tau}(x) = \frac{1}{|\{i : W_i = 1, X_i \in L\}|} \sum_{\{i:W_i=1,X_i\in L\}} Y_i - \frac{1}{|\{i : W_i = 0, X_i \in L\}|} \sum_{\{i:W_i=0,X_i\in L\}} Y_i. \quad (4)$$

Wager and Athey (2018) show that such treees can be used to grow causal forests that are consistent for $\tau(x)$. Then, given a procedure for generating a single causal tree, a causal forest generates a number B of such treees, each of which providing an estimate $\hat{\tau}_b(x)$. The forest then aggregates their predictions simply by averaging them:

$$\hat{\tau}(x) = B^{-1} \sum_{b=1}^{B} \hat{\tau}_b(x). \quad (5)$$

that they represented cheap labor force to exploit. Second, when the local labor requirement was abolished, in 2004, accompanying measures were introduced to prevent wage dumping.

3 The data

We use data from the Social protection and labour market dataset (SESAM). Beerli, Ruffner, Siegenthaler and Peri (2018) mostly used the data from the Earning Structure Survey (ESS) instead, due to their larger sample size. However, we prefer here SESAM data, due to their greater richness in terms of individual variables recorded. Moreover, a wage mobility analysis would not have been possible by using ESS data, since they do not have a panel structure (it is a repeated cross section, and it is not possible to follow the same units over time). On the contrary, SESAM data allow us to reconstruct individual wage trajectories for several years. In the SESAM dataset, indeed, for each year, retrospective information about earnings in the previous 1-4 years is recorded, thus also alleviating the issue of panel attrition. Finally, earnings data reported in the SESAM dataset are more reliable than those available in the ESS, since they are collected from administrative sources instead than self-reported.

We compute our wage mobility measures on the basis of yearly labor earnings, as usual in the wage mobility literature. Following e.g. Arellano and Bonhomme (2017) and Arellano et al. (2017), we exclude from our sample individuals reporting a wage equal to zero, as well as unemployed and self-employed individuals. Further, we restrict our sample to individuals working full-time in the period considered, in the wake of recent wage mobility studies (e.g. Bonhomme and Robin (2009)), in order to avoid that our results are distorted by variation in the intensive labor margin[2]. Summary descriptive statistics for the main variables in our dataset are reported in Table 9 in the Appendix. We thank Maurizio Bigotta (Tessin Statistical Office, USTAT) for graciously sharing the data on border/non-border municipalities. Data on the minimum distance (in minutes of driving travel time) of each municipality from the national border have been ob-

[2] At the same time, we are not able to control by the number of hours worked, by simply including this variable among the explanatory variables of wage mobility, since it is highly likely to be endogenous, i.e. to be influenced by the opening of the labor market, as it has been shown by Beerli, Ruffner, Siegenthaler and Peri (2018). This led us to the decision of dropping from our sample part-time workers.

tained via the Google API Console. Since driving is the most common commuting mean in Switzerland, we considered this as the transportation mode for the computation of all the commuting times. A potential concern about our identification strategy is that each municipality has a certain degree of autonomy and may have different trends in the relevant labor market outcomes. In order to ensure that our estimation results are not subject to such bias, we adopt the following strategy. Since the most important feature of municipal fiscal policy in Switzerland is the fiscal coefficient, i.e. the percentage of the Cantonal tax that each municipality charges on its taxpayers, we include this variable among our controls, in order to take into account any possible local fiscal shock[3]. Moreover, with the passing of time, the number and the size of the Swiss municipalities has changed due to mergers. Following Beerli, Ruffner, Siegenthaler and Peri (2018), in the present paper we will consider municipalities in year 2000 as time-invariant units.

Another potential concern is that the industry composition of the municipalities which are closer to the Swiss border may be relevantly different from that of the municipalities which are farther away from it. In order to tackle this issue, we follow the approach adopted by Beerli, Ruffner, Siegenthaler and Peri (2018), i.e. we introduce among the confounders the Bartik index, which is a weighted sum of sectorial employment growth rates. This index accounts for sector-driven demand trends that could affect regions differently due to their pre-existing industrial structure (Bartik (1991)).

[3]We thank Rapahel Parchet (Università della Svizzera italiana, Lugano CH) for graciously sharing the data on the fiscal coefficients for the years under scrutiny in the present study.

4 Results

4.1 Preliminary data analysis

Before applying the causal forest algorithm, we perform some exploratory data analysis, in order to obtain a first descriptive insight on wage dynamics in the period under scrutiny. In Figure 1 in the Appendix, we show the estimated kernel density of the wages of Swiss workers in our sample from 2001 to 2004, and we notice that the estimated density does not show any clear shift in 2002, the year in which the free movement agreement came into force. However, if we divide our wage data into border and non-border region, as in Figure 2 in the Appendix, we find a different picture. In particular, the mean log wage increased from 2001 to 2004 in the border region, and decreased in the non-border region. This is broadly consistent with the findings by Beerli, Ruffner, Siegenthaler and Peri (2018).

We further compute the transition matrices (Tables 10-13 in the Appendix) on the base of log wage deciles both for the border and the non-border region, before and after the free movement agreement (i.e. in 2001/2002 and in 2003/2004). From these transition matrices, we deduce that, in general, there is a high degree of decile immobility both before and after the agreement, and both in the border and in the non-border regions. This is true especially at the extremes of the distribution and is consistent with the findings of many previous studies on wage mobility in advanced economies (e.g. Bonhomme and Robin (2009)). One notable difference between decile mobility in the pre- and post- agreement periods is constituted by the smaller degree of immobility in the bottom wage decile in the border region after 2002. This suggests that, after the entry into force of the free movement agreement, the risk of low-paid workers of remaining stuck in the low-wage trap decreased. However, this result may mask individual heterogeneity of the treatment effect; hence, in the following we will resort to causal forest estimation in order to compute the CATEs.

4.2 Causal forest estimation results

In Table 15 in the Appendix, we report the estimated ATE with causal forest methods, and we notice that this average treatment effect turns out to be never statistically significant in any of the years under scrutiny (from 2002 to 2005)[4]. This holds in both cases in which either relative wage mobility or absolute wage mobility is considered as the dependent variable. However, the apparently not statistically significant average treatment effect may hide some relevant heterogeneity across groups of workers and/or across the wage distribution. This is what we aim at uncovering in the following, by estimating CATEs (Tables 1-8).

From Table 1, we deduce that the treatment effect for a 40-year old male worker with a high school diploma has been in most cases positive across the years and across the quantiles of the wage distribution. This means that the distance from the border enhanced wage mobility for this type of worker. The only two exceptions are a negative impact in 2002 in the upper part of the wage distribution and another negative effect in 2005 in the bottom part of the wage distribution. This means that, for example, in 2002 a 1% increase in driving travel time from the Swiss border for this individual would have caused an increase in his/her relative mobility by around 0.07% if he/she was in the bottom quartile of the 2001 wage distribution. On the other hand, the same positive impact of a 1% increase in treatment intensity on relative wage mobility for such a worker in the bottom part of the wage distribution would have been lower (between 0.01 and 0.02%) in 2003 and in 2004. We find very similar patterns of the treatment effect (both in sign and in size) in the case of a 20-year-old worker (either male or female) who completed high school (Table 5 and Table 6).

[4]Of course, it would be interesting to investigate the medium and long-term impact of this policy change on individual wage mobility patterns. However, in order to preserve exogeneity of the confounders, we evaluate wage mobility at different percentiles of the pre-treatment wage distribution (i.e. the wage distribution in year 2001). Due to sample attrition in the SESAM dataset, information on individual wage in year 2001 is only available for a number of individuals which is decreasing over time. As a consequence, it is not possible to run meaningful estimates for the years after 2005, due the excessive reduction in sample size.

The picture is slightly different when considering the case of individuals who completed an educational level lower than high school. The main features of the CATEs computed in the case of high school education are preserved (i.e. impact in most cases is positive), but we find evidence of a negative treatment effect in almost all wage quantiles in year 2003 (Table 3 and Table 4), both for males and for females. The same feaure is also found in the case of a 40-year-old female worker with high school diploma (Table 2).

Finally, in Table 7 we find that the estimated CATEs for a foreign-born individual follow a very similar pattern across the years and across the wage distribution of those of a native worker of the same age and educational level (see Table 1). As a robustness check, in Table 8, we computed CATEs in the case in which the dependent variable is absolute wage mobility instead of relative wage mobility. As mentioned above, we define absolute wage mobility as the percentage change in wages from one year to the following one. From the estimation results, we deduce that, for a 40-year-old male worker with high school diploma, the sign of the estimated treatment effects are in most cases the same (in the years considered and across the wage distribution) as in the case in which the dependent variable is relative wage mobility.

We conclude that the zero ATEs estimated with the causal forest in Table 15 mask statistically significant treatment effects, which in different years and for different types of workers have been positive in some parts of the wage distribution and negative in some other parts of it.

Our results are complementary to those obtained by Beerli, Ruffner, Siegenthaler and Peri (2018), in the sense that, whereas they find that the liberalization of the status of cross-border workers lead to an increase in the wage level for highly educated workers, we find that the same regional policy change led in most cases to an increase in positional or relative wage mobility for workers with a high educational level.

5 Conclusion

Wage mobility is a distinctive feature of an economy. It is directly related to employees' satisfaction and productivity and it determines long-term trends in income inequality. In the present paper we aimed at assessing the short-term impact of an opening of the labor market, i.e. the entry into force of the free movement agreement, which took place in Switzerland since 2002, on the degree of relative wage mobility.

By applying causal forest methods in the spirit of Wager and Athey (2018), we computed the conditional average treatment effects (CATEs) for different groups of workers, in order to assess which individuals have been most affected by this regional policy change. Our main findings are that: (i) simple mean estimation of the impact masks substantial heterogeneity across age, gender and education groups, (ii) the impact of the treatment (i.e. the driving travel time from the Swiss border) on relative wage mobility has been mostly positive for workers who completed high school, (iii) on the contrary, we found some evidence of a negative impact of the treatment on wage mobility at the bottom of the wage distribution for less-educated workers. This finding entails a higher risk of remaining stuck in the low-pay trap for those individuals.

Our results are complementary to those of Beerli, Ruffner, Siegenthaler and Peri (2018). Indeed, the generally positive impact of the policy change on the absolute wage level found by the authors is not incompatible with a decline in positional (relative) wage mobility for some group of workers[5]. the workers remain exactly the same as in the previous year. It would be interesting now to assess the channels through which an opening of the labor market leads to a decline in relative wage mobility for some categories of workers. A limitation of the present work is that, as usual in the earnings mobility literature, we rely on the missing-at-random assumption. In the model presented, we do not account for transitions into and out of unemployment. This con-

[5]It is possible, that, for example, all wages in a country rise in a given year, but the relative positions of. In such a case, relative wage mobility would be equal to zero, even if wage levels of each worker have risen.

stitutes scope for future research. Another relevant avenue for further research is the analysis of the transmission channels and mechanisms through which the degree of labor market openness to inflows of foreign workers influences individual relative wage mobility patterns.

References

1. Abramitzky, R., Boustan, L. P., & Eriksson, K. (2014). A nation of immigrants: Assimilation and economic outcomes in the age of mass migration. Journal of Political Economy, 122(3), 467-506.

2. Aydemir, A., & Borjas, G. J. (2011). Attenuation bias in measuring the wage impact of immigration. Journal of Labor Economics, 29(1), 69-112.

3. Atkinson, A. B., T. Piketty, and E. Saez. 2011. Top Incomes in the Long Run of History. Journal of Economic Literature, 49(1): 3-71.

4. Arellano, M., & Bonhomme, S. (2017). Quantile Selection Models with an Application to Understanding Changes in Wage Inequality. Econometrica, 85(1), 1-28.

5. Arellano, M., Blundell, R., & Bonhomme, S. (2017). Earnings and consumption dynamics: a nonlinear panel data framework. Econometrica, 85(3), 693-734.

6. Athey, S., & Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. Proceedings of the National Academy of Sciences, 113(27), 7353-7360.

7. Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the US Labor Market. The American Economic Review, 96(2), 189-194.

8. Bartik, T. J. (1991). Who Benefits from State and Local Economic Development Policies?. Books from Upjohn Press.

9. Beerli, A., Ruffner, J., Siegenthaler, M., & Peri, G. (2018). The Abolition of Immigration Restrictions and the Performance of Firms and Workers: Evidence from Switzerland (No. w25302). National Bureau of Economic Research.

10. Bertrand, M., Crepon, B., Marguerie, A., & Premand, P. (2017). Contemporaneous and Post-Program Impacts of a Public Works Program: Evidence from Cote d'Ivoire. Working paper.

11. Bijwaard, G. E., Schluter, C., & Wahba, J. (2014). The impact of labor market dynamics on the return migration of immigrants. Review of Economics and Statistics, 96(3), 483-494.

12. Blau, F. D., & Kahn, L. M. (2015). Immigration and the Distribution of Incomes. In Handbook of the economics of international migration (Vol. 1, pp. 793-843). North-Holland.

13. Bonhomme, S., and Robin, J. M. (2009). Assessing the equalizing force of mobility using short panels: France, 1990-2000. The Review of Economic Studies, 76(1), 63-92.

14. Bonke, T., Corneo, G., & Luethen, H. (2014). Lifetime earnings inequality in Germany. Journal of Labor Economics, 33(1), 171-208.

15. Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. The quarterly journal of economics, 118(4), 1335-1374.

16. Borjas, G. J., Grogger, J., & Hanson, G. H. (2008). Imperfect substitution between immigrants and natives: a reappraisal (No. w13887). National Bureau of Economic Research.

17. Buchinsky, M., Gotlibovski, C., & Lifshitz, O. (2014). Residential location, work location, and labor market outcomes of immigrants in israel. Econometrica, 82(3), 995-1054.

18. Cadena, B. C. (2013). Native competition and low-skilled immigrant inflows. Journal of Human Resources, 48(4), 910-944.

19. Card, D. (2009). Immigration and inequality. American Economic Review, 99(2), 1-21.

20. Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. Journal of Labor Economics, 19(1), 22-64.

21. Card, D., & DiNardo, J. (2000). Do immigrant inflows lead to native outflows?. American Economic Review, 90(2), 360-367.

22. Card, D. (1990). The impact of the Mariel boatlift on the Miami labor market. ILR Review, 43(2), 245-257.

23. Cattaneo, C., Fiorio, C. V., & Peri, G. (2015). What Happens to the Careers of European Workers When Immigrants "Take Their Jobs"?. Journal of Human Resources, 50(3), 655-693.

24. Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. The Quarterly Journal of Economics, 129(4), 1553-1623.

25. Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. The Journal of Economic Perspectives, 27(3), 79-102.

26. Davis, J., & Heller, S. B. (2017). Using Causal Forests to Predict Treatment Heterogeneity: An Application to Summer Jobs. American Economic Review, 107(5), 546-50.

27. Dustmann, C., Schonberg, U., & Stuhler, J. (2017). Labor supply shocks, native wages, and the adjustment of local employment. The Quarterly Journal of Economics, 132(1), 435-483.

28. Dustmann, C., Schonberg, U., & Stuhler, J. (2016). The impact of immigration: Why do studies reach such different results?. The Journal of Economic Perspectives, 30(4), 31-56.

29. Dustmann, C., Frattini, T., & Preston, I. P. (2012). The effect of immigration along the distribution of wages. Review of Economic Studies, 80(1), 145-173.

30. Foged, M., & Peri, G. (2016). Immigrants' effect on native workers: New analysis on longitudinal data. American Economic Journal: Applied Economics, 8(2), 1-34.

31. Gabaix, X., Lasry, J. M., Lions, P. L., & Moll, B. (2016). The dynamics of inequality. Econometrica, 84(6), 2071-2111.

32. Gerfin, M., & Kaiser, B. (2010). The effects of immigration on wages: An application of the structural skill-cell approach. Swiss Journal of Economics and Statistics, 146(4), 709-739.

33. Glitz, A. (2012). The labor market impact of immigration: A quasi-experiment exploiting immigrant location rules in Germany. Journal of Labor Economics, 30(1), 175-213.

34. Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. The American Economic Review, 99(2), 58-63.

35. Imbens, G.W. (2004). Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review, The Review of Economics and Statistics, 86, 4-29.

36. Kerr, W. R., & Lincoln, W. F. (2010). The supply side of innovation: H-1B visa reforms and US ethnic invention. Journal of Labor Economics, 28(3), 473-508.

37. Kleinberg, J., Ludwig J., Mullainathan, S. and Obermeyer, Z. (2015). Prediction Policy Problems. American Economic Review: Papers & Proceedings, 105(5), pp.491-495.

38. Kugler, A., & Yuksel, M. (2008). Effects of low-skilled immigration on US natives: evidence from Hurricane Mitch (No. w14293). National Bureau of Economic Research.

39. Lechner, M. (2001). Identification and Estimation of Causal Effects of Multiple Treatments under the Conditional Independence Assumption, in: M. Lechner and F. Pfeiffer (eds.), Econometric Evaluation of Active Labour Market Policies, 43-58, Heidelberg: Physica.

40. Lefgren, L., Sims, D., & Lindquist, M. J. (2012). Rich dad, smart dad: Decomposing the intergenerational transmission of income. Journal of Political Economy, 120(2), 268-303.

41. Longhi, S., Nijkamp, P., & Poot, J. (2005). A meta-analytic assessment of the effect of immigration on wages. Journal of economic surveys, 19(3), 451-477.

42. Losa, Fabio B., Maurizio Bigotta et Oscar Gonzalez 2014. La Libre Circulation: Joies ou Douleurs. Evaluation des Effets sur le Marché du Travail Suisse de l'Abolition de la Priorité en Matière d'Emploi Accordé aux Travailleurs Indigènes. Office de Statistique du Canton du Tessin.

43. McHenry, P. (2015). Immigration and the human capital of natives. Journal of Human Resources, 50(1), 34-71.

44. Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. Journal of Economic Perspectives, 31(2), 87-106.

45. Nybom, M., & Stuhler, J. (2016). Biases in standard measures of intergenerational income dependence. Journal of Human Resources, 0715-7290R.

46. Olney, W. W. (2015). Remittances and the wage impact of immigration. Journal of Human Resources, 50(3), 694-727.

47. Ortega, F., & Peri, G. (2014). Openness and income: The roles of trade and migration. Journal of International Economics, 92(2), 231-251.

48. Ottaviano, G. I., & Peri, G. (2012). Rethinking the effect of immigration on wages. Journal of the European economic association, 10(1), 152-197.

49. Parchet, R. (2018). Are Local Tax Rates Strategic Complements or Strategic Substitutes? Working paper. Forthcoming in the American Economic Journal: Economic Policy.

50. Patel, K., & Vella, F. (2013). Immigrant networks and their implications for occupational choice and wages. Review of Economics and Statistics, 95(4), 1249-1277

51. Peri, G. (2016). Immigrants, productivity, and labor markets. The Journal of Economic Perspectives, 30(4), 3-29.

52. Peri, G. (2012). The effect of immigration on productivity: Evidence from US states. Review of Economics and Statistics, 94(1), 348-358.

53. Peri, G., Shih, K., & Sparber, C. (2015). STEM workers, H-1B visas, and productivity in US cities. Journal of Labor Economics, 33(S1), S225-S255.

54. Peri, G., & Sparber, C. (2011). Highly educated immigrants and native occupational choice. Industrial Relations: a journal of economy and society, 50(3), 385-411.

55. Piketty, T., & Saez, E. (2003). Income inequality in the United States, 1913-1998. The Quarterly journal of economics, 118(1), 1-41.

56. Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.

57. Roy, A. D. (1951). Some thoughts on the distribution of earnings. Oxford economic papers, 3(2), 135-146.

58. Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. Journal of educational Psychology, 66(5), 688.

59. Smith, C. L. (2012). The impact of low-skilled immigration on the youth labor market. Journal of Labor Economics, 30(1), 55-89.

60. Wager, S., & Athey, S. (2018). Estimation and inference of heterogeneous treatment effects using random forests. Journal of the American Statistical Association, (forthcoming).

Table 1: CATE for a 40-year-old man who completed high school. Dependent variable is relative wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0699***	0.0748***	0.0394***	-0.0227***	-0.0200***
	(0.0020)	(0.0014)	(0.0006)	(0.0006)	(0.0004)
2003	0.0025***	0.0113***	0.0006	0.0061***	-0.0103***
	(0.0005)	(0.0004)	(0.0005)	(0.0003)	(0.0008)
2004	0.0172***	0.0170***	0.0185***	0.0071***	0.0253***
	(0.0005)	(0.0004)	(0.0003)	(0.0006)	(0.0002)
2005	-0.0075***	-0.0073***	0.0095***	0.0081***	0.0137***
	(0.0007)	(0.0003)	(0.0004)	(0.0002)	(0.0001)

In all the cases presented above, we consider an individual who is not foreign-born, and works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

Table 2: CATE for a 40-year-old woman who completed high school. Dependent variable is relative wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0211***	0.0186***	0.0342***	-0.0348***	-0.0350***
	(0.0014)	(0.0005)	(0.0010)	(0.0007)	(0.0004)
2003	-0.0085***	0.0025***	-0.0087***	-0.0006**	-0.0131***
	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)
2004	0.0150***	0.0157***	0.0124***	0.0016*	0.0163***
	(0.0004)	(0.0003)	(0.0003)	(0.0009)	(0.0003)
2005	-0.0167***	-0.0116***	0.0176***	0.0131***	0.0227***
	(0.0004)	(0.0003)	(0.0005)	(0.0005)	(0.0002)

In all the cases presented above, we consider an individual who is not foreign-born, and works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

Table 3: CATE for a 40-year-old man who completed an educational level lower than high school. Dependent variable is relative wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0805***	0.0817***	0.0249***	-0.03965***	-0.0330***
	(0.0028)	(0.0021)	(0.0006)	(0.00041)	(0.0003)
2003	-0.0117***	-0.0006**	-0.0183***	0.0029***	-0.0174***
	(0.0008)	(0.0003)	(0.0005)	(0.0003)	(0.0014)
2004	0.0233***	0.0009***	0.0119***	-0.0195***	0.0068***
	(0.0008)	(0.0003)	(0.0003)	(0.0004)	(0.0002)
2005	-0.0079***	-0.0083***	0.0097***	0.0163***	0.0190***
	(6.40E-04)	(5.32E-04)	(2.11E-04)	(1.36E-04)	(7.68E-05)

In all the cases presented above, we consider an individual who is not foreign-born, and works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

Table 4: CATE for a 40-year-old woman who completed an educational level lower than high school. Dependent variable is relative wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0294***	0.0147***	0.0248***	-0.0398***	-0.0383***
	(0.0012)	(0.0004)	(0.0006)	(0.0005)	(0.0003)
2003	-0.0205***	-0.0022***	-0.0326***	0.0045***	-0.0116***
	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0009)
2004	0.0182***	-0.0021***	0.0061***	-0.0329***	-0.0036***
	(0.0007)	(0.0003)	(0.0003)	(0.0009)	(0.0002)
2005	-0.0168***	-0.0139***	0.0216***	0.0167***	0.0267***
	(0.0005)	(0.0002)	(0.0005)	(0.0003)	(0.0002)

In all the cases presented above, we consider an individual who is not foreign-born, and works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

Table 5: CATE for a 20-year-old man who completed high school. Dependent variable is relative wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0437***	0.0279***	0.0331***	-0.0195***	-0.0135***
	(0.0009)	(0.0008)	(0.0006)	(0.0006)	(0.0005)
2003	0.0216***	0.0015***	0.0043***	0.0090***	-0.0021***
	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0002)
2004	0.0024**	0.0513***	0.0155***	0.0202***	0.0246***
	(0.0011)	(0.0010)	(0.0010)	(0.0008)	(0.0009)
2005	-0.0013**	0.0120***	-0.0105***	0.0124***	0.0097***
	(0.0005)	(0.0002)	(0.0003)	(0.0003)	(0.0002)

In all the cases presented above, we consider an individual who is not foreign-born, and works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

Table 6: CATE for a 20-year-old woman who completed high school. Dependent variable is relative wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0299***	-0.0069***	0.0299***	-0.0224***	-0.0238***
	(0.0008)	(0.0005)	(0.0008)	(0.0006)	(0.0004)
2003	0.0068***	-0.0055***	0.0015***	0.0034***	-0.0044***
	(4.57E-04)	(3.58E-04)	(1.76E-04)	(1.35E-04)	(9.86E-05)
2004	0.0022**	0.0373***	0.0055***	0.0102***	0.0165***
	(0.0011)	(0.0015)	(0.0012)	(0.0009)	(0.0007)
2005	-0.0007	0.0147***	-0.0197***	0.0123***	0.0148***
	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0003)

In all the cases presented above, we consider an individual who is not foreign-born, and works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

Table 7: CATE for a 40-year-old foreign-born man who completed high school. Dependent variable is relative wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0716***	0.0698***	0.0423***	-0.0189***	-0.0166***
	(0.0019)	(0.0012)	(0.0007)	(0.0008)	(0.0004)
2003	-0.0126***	0.0218***	0.0130***	0.0147***	-0.0140***
	(0.0008)	(0.0003)	(0.0004)	(0.0006)	(0.0005)
2004	0.0145***	0.0067***	0.0187***	0.0003	0.0154***
	(0.0005)	(0.0005)	(0.0004)	(0.0006)	(0.0002)
2005	-0.0156***	-0.0067***	-0.0035***	0.0052***	0.0092***
	(5.84E-04)	(2.99E-04)	(2.80E-04)	(2.55E-04)	(8.97E-05)

In all the cases presented above, we consider an individual who works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

Table 8: CATE for a 40-year-old man who completed high school. Dependent variable is absolute wage mobility.

	Q_0.05	Q_0.25	Q_0.50	Q_0.75	Q_0.95
2002	0.0023***	0.0020***	0.0005***	-0.0002***	-0.0002***
	(8.47E-04)	(1.14E-06)	(1.33E-07)	(1.06E-07)	(1.82E-07)
2003	-0.0059***	0.0004***	0.0001***	0.0002***	-0.0005***
	(2.73E-05)	(1.48E-07)	(1.59E-07)	(2.91E-08)	(1.13E-07)
2004	-0.0028***	0.0005***	0.0004***	0.0004***	0.0005***
	(1.78E-05)	(2.15E-07)	(1.17E-07)	(1.52E-07)	(1.27E-07)
2005	-0.0010***	-0.0002***	0.0002***	0.00002***	-0.0001***
	(2.77E-05)	(3.30E-07)	(3.42E-08)	(6.78E-08)	(1.46E-07)

In all the cases presented above, we consider an individual who is not foreign-born, and works in a firm of intermediate size. All continuous control variables (except past log wage) are kept at their average value in the sample. Each column stands for a log wage quantile.

In all the CATE estimates, the splitting rule adopted is the honest causal tree splitting rule defined by Athey and Imbens (2016). It is an adjusted mean square error criterion, which rewards a split finding heterogeneity in treatment effects and penalizes a split increasing variance in leaf estimates. Standard errors are computed via jackknifing. Given that in our case the treatment is continous, what is effectively estimateed is an average partial effect, i.e. $Cov[Y, W|X = x]/Var[W|X = x]$, which is interpreted as a treatment effect given unconfoundedness.

Appendix

A. The Bilateral Agreements

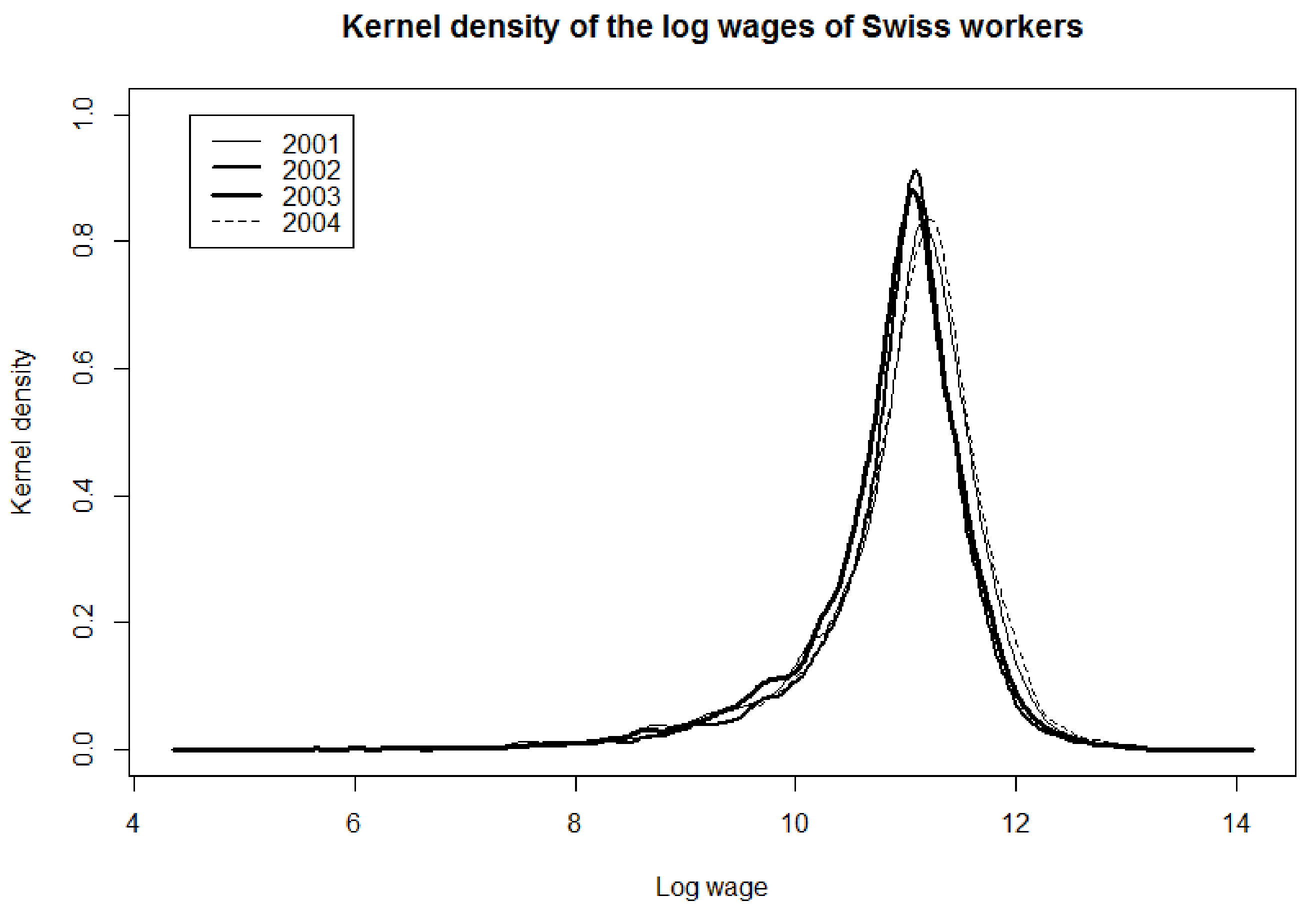
The Bilateral Agreements I between Switzerland and the European Union were signed in June 1999 and came into force in 2002. They included seven liberalization agreements: free movement of persons, technical barriers to trade, agricultural products, overland transport, public procurement, scientific and technological cooperation. A second set of Bilateral Agreements was signed in October 2004 and approved in referendum in June 2005. In 2002 there still were restrictions on the free movement of people, which were later abolished. In particular, the priority requirement, which also concerned cross-border workers, was eliminated in 2004, whereas quotas (which never concerned cross-border workers) were abolished in 2007.

B. Descriptive data analysis

Table 9: Descriptive statistics for the period 2001-2005, SLFS and SESAM pooled data

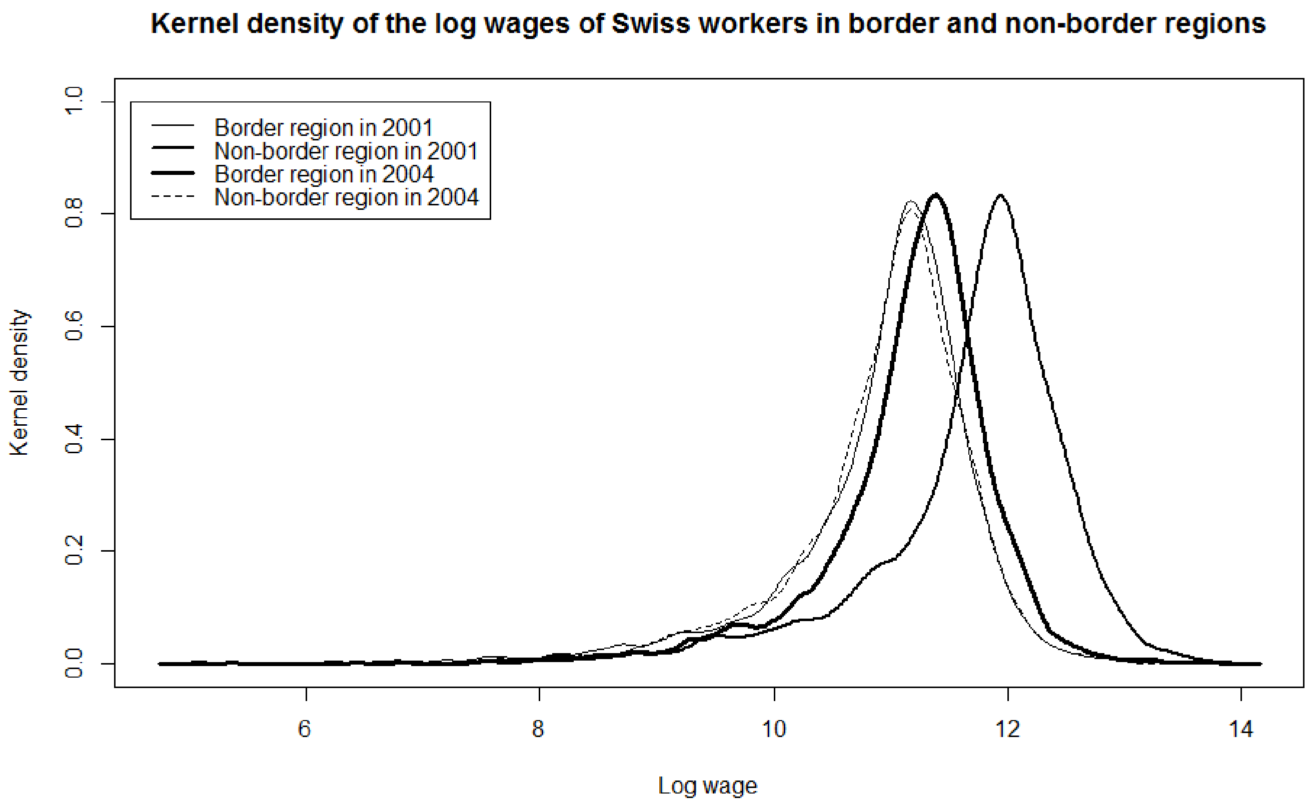
	N. obs.	Average	St. Dev.	Min	Max
Age	52930	41.781	10.991	18	65
Female dummy	52930	0.469	0.499	0	1
Married dummy	52930	0.549	0.498	0	1
Foreign-citizen dummy	52930	0.383	0.486	0	1
General education dummy	52930	0.013	0.112	0	1
Apprenticeship dummy	52930	0.363	0.481	0	1
High school or professional diploma dummy	52930	0.087	0.282	0	1
University dummy	52930	0.152	0.359	0	1
Public sector dummy	52930	0.218	0.413	0	1
Log annual wage	52930	10.933	0.797	3.912	15.684
Small enterprise (<20 employees)	52930	0.098	0.297	0	1
Medium enterprise (between 20 and 49)	52930	0.174	0.379	0	1
Medium-large ent. (between 50 and 99)	52930	0.127	0.333	0	1
Large enterprise (>100 employees)	52930	0.397	0.489	0	1

Figure 1: Estimated density of log wages of Swiss workers in 2002-2005 (data on border and non-border regions pooled together)



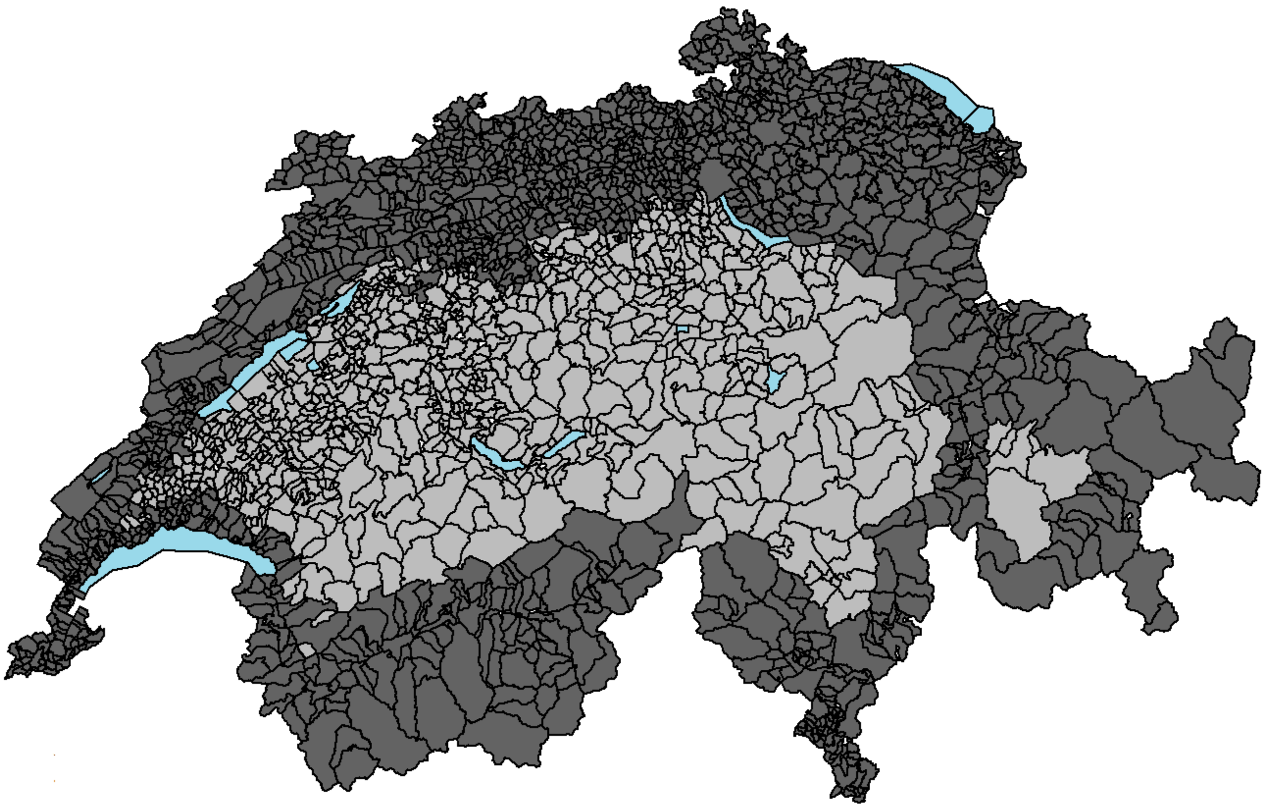
Data source: Swiss Labor Force Survey (SLFS).

Figure 2: Estimated density of log wages of Swiss workers in border and non-border regions



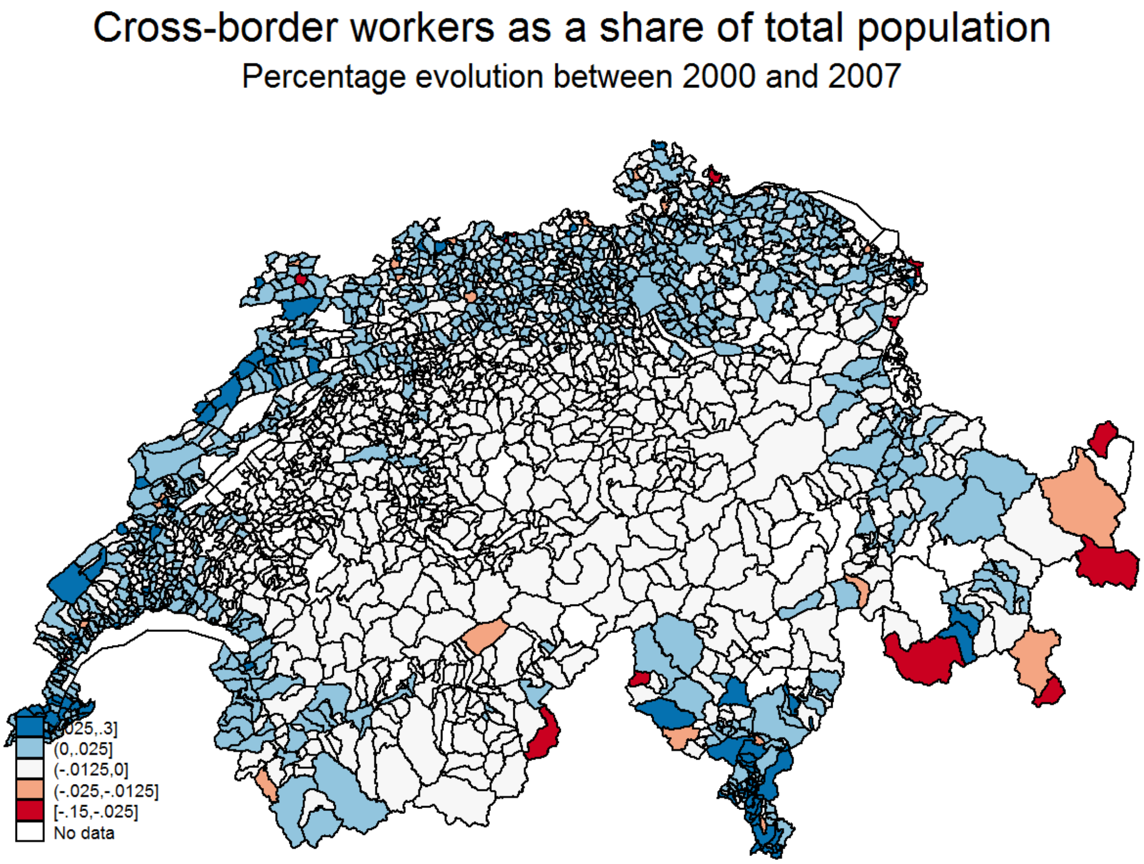
Data source: Swiss Labor Force Survey (SLFS).

Figure 3: Municipalities in the border region (dark grey) and in the non-border region (light grey)



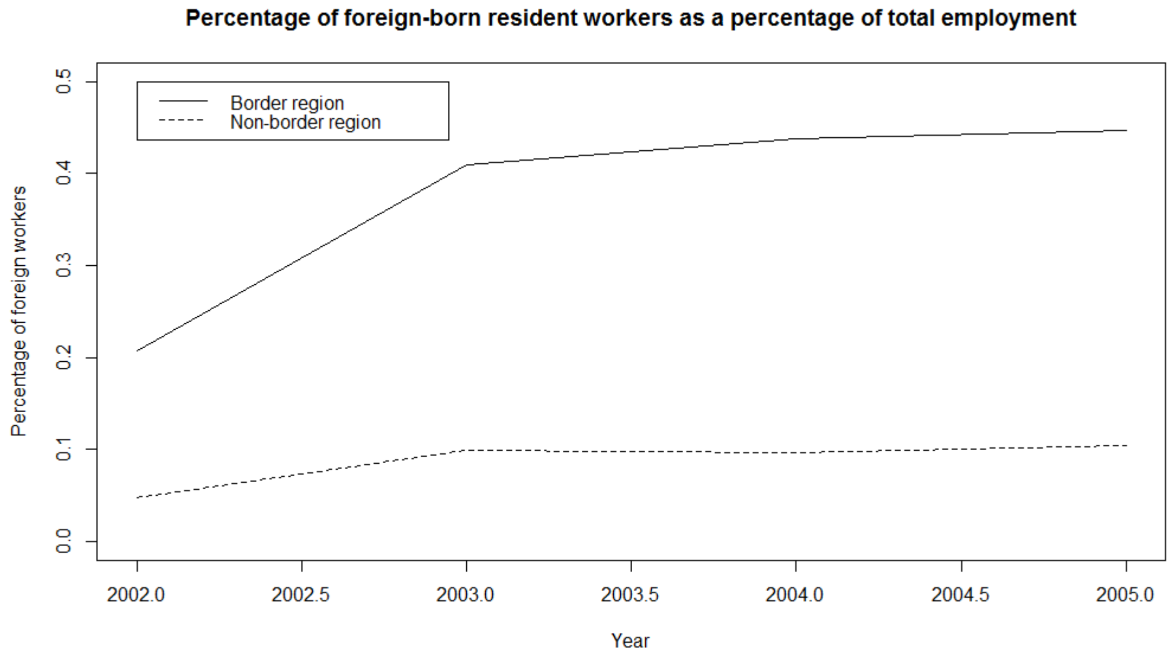
Note that border regions do not overlap completely with cantonal borders. Data source: UST.

Figure 4: Evolution of the number of cross-border workers in Switzerland, 2000-2007



In this figure, the difference in the share of cross-border workers on the total population of each municipality between 2000 and 2007 is reported. Data are from the Federal Statistical Office.

Figure 5: Evolution of the number of foreign workers in the border and non-border regions, 2002-2007



This figure shows that both in the border and in the non-border Swiss region, the number of resident foreign-born workers as a share of total employment nearly doubled after the policy change in 2002. In the border region the liberalization of the status of cross-border workers did not offset neither discouraged migration flows. Data from the Swiss Labor Force Survey.

Table 10: Wage decile transition matrix, non-border region, 2003/2004, n=2769

	1	2	3	4	5	6	7	8	9	10
1	**0.751**	0.173	0.032	0.018	0.018	0.000	0.000	0.004	0.004	0.000
2	0.166	**0.592**	0.134	0.058	0.018	0.018	0.007	0.004	0.004	0.000
3	0.025	0.173	**0.565**	0.162	0.047	0.022	0.000	0.004	0.004	0.000
4	0.014	0.022	0.159	**0.551**	0.214	0.018	0.014	0.000	0.004	0.004
5	0.011	0.025	0.029	0.129	**0.561**	0.165	0.054	0.018	0.007	0.000
6	0.014	0.011	0.029	0.036	0.112	**0.594**	0.167	0.025	0.007	0.004
7	0.007	0.007	0.014	0.014	0.022	0.141	**0.625**	0.152	0.011	0.007
8	0.007	0.004	0.022	0.018	0.007	0.025	0.116	**0.664**	0.130	0.007
9	0.004	0.000	0.004	0.007	0.004	0.018	0.007	0.116	**0.740**	0.101
10	0.000	0.004	0.004	0.004	0.004	0.000	0.011	0.011	0.087	**0.877**

Table 11: Wage decile transition matrix, border region, 2003/2004, n=9062

	1	2	3	4	5	6	7	8	9	10
1	**0.688**	0.194	0.062	0.026	0.011	0.007	0.006	0.004	0.001	0.001
2	0.141	**0.557**	0.183	0.058	0.029	0.015	0.006	0.008	0.002	0.001
3	0.043	0.139	**0.556**	0.179	0.044	0.017	0.009	0.007	0.004	0.002
4	0.032	0.043	0.110	**0.543**	0.207	0.043	0.015	0.005	0.001	0.000
5	0.028	0.024	0.052	0.106	**0.564**	0.180	0.025	0.018	0.002	0.000
6	0.027	0.014	0.017	0.037	0.109	**0.596**	0.166	0.028	0.006	0.001
7	0.021	0.014	0.013	0.019	0.026	0.111	**0.630**	0.151	0.011	0.003
8	0.010	0.004	0.010	0.014	0.010	0.021	0.120	**0.664**	0.137	0.009
9	0.006	0.003	0.000	0.007	0.003	0.010	0.022	0.102	**0.757**	0.091
10	0.007	0.004	0.004	0.001	0.001	0.001	0.001	0.009	0.082	**0.890**

Table 12: Wage decile transition matrix, non-border region, 2001/2002, n=2057

	1	2	3	4	5	6	7	8	9	10
1	**0.757**	0.121	0.049	0.015	0.015	0.000	0.024	0.000	0.005	0.015
2	0.189	**0.568**	0.131	0.063	0.010	0.015	0.010	0.010	0.005	0.000
3	0.015	0.184	**0.568**	0.121	0.063	0.019	0.015	0.015	0.000	0.000
4	0.029	0.049	0.166	**0.517**	0.146	0.044	0.034	0.010	0.000	0.005
5	0.000	0.019	0.044	0.199	**0.544**	0.131	0.049	0.005	0.005	0.005
6	0.005	0.010	0.029	0.049	0.189	**0.519**	0.165	0.029	0.005	0.000
7	0.005	0.015	0.015	0.020	0.029	0.215	**0.546**	0.127	0.020	0.010
8	0.000	0.010	0.000	0.005	0.010	0.039	0.136	**0.641**	0.141	0.019
9	0.000	0.015	0.005	0.000	0.000	0.010	0.015	0.146	**0.728**	0.083
10	0.000	0.015	0.000	0.000	0.000	0.010	0.000	0.020	0.093	**0.863**

Table 13: Wage decile transition matrix, border region, 2001/2002, n=5619

	1	2	3	4	5	6	7	8	9	10
1	**0.762**	0.135	0.041	0.011	0.014	0.011	0.009	0.007	0.007	0.004
2	0.144	**0.593**	0.172	0.044	0.018	0.018	0.005	0.004	0.000	0.002
3	0.034	0.177	**0.561**	0.145	0.050	0.016	0.004	0.009	0.002	0.004
4	0.016	0.041	0.127	**0.581**	0.166	0.044	0.009	0.014	0.002	0.000
5	0.005	0.018	0.045	0.132	**0.540**	0.202	0.045	0.011	0.002	0.000
6	0.007	0.011	0.028	0.044	0.132	**0.530**	0.205	0.034	0.007	0.002
7	0.007	0.012	0.014	0.018	0.050	0.130	**0.570**	0.169	0.025	0.004
8	0.009	0.005	0.009	0.011	0.018	0.019	0.125	**0.610**	0.178	0.016
9	0.011	0.007	0.004	0.009	0.007	0.013	0.023	0.109	**0.685**	0.133
10	0.004	0.000	0.004	0.004	0.005	0.014	0.009	0.027	0.096	**0.838**

C Causal forest estimation results

We use the "grf" package which implements causal forests as introduced in Wager and Athey (2018). As far as the tuning of the causal forest is concerned, following Bertrand et al. (2017) we set the number of trees in the forest equal to 10'000, the minimum number of treatment and control units per leaf is equal to 10, and the fraction of the subsample used to build each tree, as well as the fraction of the subsample used for training, is 0.5.

Table 14: List of baseline covariates used as features in the causal forest algorithm

Variable description	Type
Bartik index	continuous
Fiscal coefficient	continuous
Log past wage	continuous
Married	binary
Foreign-born	binary
Working in public sector	binary
Dummies for the size of the firm (4)	binary
Dummies for the education level (4)	binary
Gender	binary
Age	continuous
Distance from the border in km	continuous
Canton dummies (25)	binary

Note that past wage refers to pre-treatment wage, i.e. wage in 2001.

Table 15: Estimated average partial effects of the continuous treatment on wage mobility of native workers

	Pooled data	2002	2003	2004	2005
Relative mobility	-0.0007 (0.0038)	-0.0010 (0.0092)	0.0047 (0.0061)	0.0037 (0.0077)	0.0061 (0.0071)
Absolute mobility	-0.0007 (0.0007)	-0.0011 (0.0026)	0.0009 (0.0010)	-0.0012 (0.0014)	-0.0004 (0.0009)