Effects of Mandatory Job Postings on Labor Market Outcomes

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Abstract

This paper studies the effects of a Job Vacancy Notice Obligation (JVNO) policy, which aims to support resident job seekers in high unemployment occupations in Switzerland. Specifically, this policy mandates firms that want to hire in these occupations to post vacancies on a designated online local platform and prohibits them from advertising the vacancy elsewhere for five days. Adopting a regression-discontinuity-design (RDD) which contrasts occupations on either side of the unemployment threshold, we find a significant increase in the number of vacancies posted as well as of posting firms for treated occupations. These effects are stronger for firms that have never posted online before the policy was introduced. We also find significant and strong increases in employment, suggesting that increased posting is not just due to firms switching from informal hiring to posting jobs online. The JVNO policy exhibits substantial positive effects on match efficiency, by bolstering job search programs for unemployed workers.

Keywords: ALMP, Labor Demand, Labor Market Efficiency

JEL Codes: J08, J23, J64

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1 Introduction

The matching process between job seekers and employers plays a crucial role in determining labor market outcomes, yet inefficiencies in this process remain a persistent challenge. On one hand, job seekers often face unclear pathways to discovering available opportunities and navigating application processes. On the other hand, employers struggle to attract suitable candidates and expedite hiring decisions. These frictions contribute to the coexistence of high unemployment rates alongside high vacancy rates. In response to these challenges, policymakers implemented policies to improve job search. Most common examples are training programs, job search assistance, and subsidies to incentivize active job search. The effectiveness of these programs can vary widely, depending on how well they are tailored to the needs of the local job market and the specific sectors they are intended to serve.[1] More recently, low-cost automated and AI driven interventions have been used to expand the search of job seekers with positive effects on employment, particularly for less-educated workers (Belot et al., 2019; Le Barbanchon et al., 2023).

On the other hand, part of the inefficiency might be attributable to the demand side, in particular to the use of informal hiring practices. Informal hiring often depends on internal staff referrals, personal networks, coaches, poaching former employees, or recruitment consultants. This creates a closed system that excludes individuals outside the firm or its immediate connections, leaving many unaware of available opportunities.[2] In contrast, formal hiring involves publicly posting vacancies online and selecting candidates through standardized procedures. This approach reduces dependence on personal networks, benefiting less-connected workers, particularly immigrants who often lack established social ties in the host country, and fosters more equitable opportunities for all job seekers. Furthermore, informal hiring often operates outside the bounds of hiring laws, bypassing regulations such as wage transparency in job postings (Bamieh and Ziegler, 2024; Frimmel et al., 2024; Škoda, 2022) or adherence to anti-discrimination laws in vacancy announcements (Kuhn and Shen, 2013, 2023; Card et al., 2024). However, formal hiring can be more expensive for firms, particularly small businesses, due to the costs associated with broader outreach efforts and the implementation of structured assessment processes.

Despite the importance of firms' decisions in the hiring process, policies that attempt to reduce inefficiencies and discrimination by targeting the firm's recruiting are rare (Bartik, 2001; Algan et al., 2020). This set of policies includes hiring credits (Neumark and Grijalva, 2017), payroll incentives (Ku et al., 2020) or hiring quotas (McCrary, 2007) to stimulate local employment or disadvantaged groups. Moreover, there is no evidence on how mandating firms to use formal hiring practices impacts the labor market.

[1] For more information on Active Labor Market Policies (ALMPs) evaluations see Lalive et al. (2008), Caliendo and Schmidl (2016), and Kluve et al. (2019). For an extensive Meta analysis see Card et al. (2018)

[2] See Montgomery (1991); Pistaferri (1999); Bayer et al. (2008); Hensvik and Skans (2016) for theoretical and empirical evidence on the effects of hiring through network.

This paper uncovers the labor market effects of a policy mandating firms to post vacancies in specific occupations experiencing high unemployment rates. Specifically, we investigate the impact on firms and workers of the The Swiss Job Vacancy Notification Obligation (JVNO), a policy introduced by the federal government with aim to improve job search outcomes for unemployed locals. The policy requires firms to advertise vacancies in designated occupations on a governmental platform "jobroom.ch" and prohibited them from advertising the vacancy elsewhere for five days. During this period the job postings are accessible exclusively to registered jobseekers. The occupations covered by the policy are determined annually based on the occupation-specific unemployment rate, offering potential heterogeneity for investigation.

We leverage rich administrative and web-scraped data on workers, firms and job postings and perform two main empirical exercise. In the first part of the analysis implement a regression-discontinuity-design comparing occupations covered by JVNO with the others in terms of labor demand and employment. In the second part of the analysis we exploit the spatial heterogeneity between 101 commuting zones and assess the total employment effects of the policy and its impact on the migration.

Our findings reveal that job postings increase by approximately 17 percent and the number of firms posting raises by almost 13 percent at the policy threshold. As expected, this growth is particularly pronounced for postings in the *Jobroom.ch* portal, but we record positive spillovers also on vacancies advertised on other websites. A substantial portion of the increase stems from the entry of firms posting vacancies online for the first time, highlighting the policy's role in expanding participation in the formal hiring channel.

One potential concern is that the observed increase in postings might not reflect higher labor demand but rather a shift from informal to formal hiring methods. To address this, we analyze employment trends and find that employment significantly increases by about 9 percent in the protected occupations. This indicates that the policy-driven increase in postings largely corresponds to genuine job creation rather than a mere reclassification of hiring practices.

A second potential objection is that the observed employment increases could result from job seekers shifting from occupations below the policy threshold to similar occupations just above it, representing a substitution effect rather than genuine employment growth. To address this concern, we analyze employment patterns across Switzerland's 101 commuting zones, examining whether employment growth aligns with zones' exposure to occupations covered by the JVNO. Our findings show that commuting zones with the highest exposure experience the strongest employment increases and non-negative effects on earnings. Notably, the employment effects are more pronounced for foreign citizens, underscoring the policy's role in promoting labor market inclusivity for historically under-represented groups. We also find positive effects on migration and positive employment effects for immigrants indicating that the formal hiring might have also attracted workers from abroad.

This paper contributes to several strands of the literature. Primarily, it relates to the literature that studies the effectiveness of policies aiming at easing the match in the labor market. Most of this literature looks at the labor supply side of the market analyzing the effects of job search assistance programs. This line of research is well-documented by a plethora of studies finding that job search assistance programs are relatively effective compared to public sector employment programs, which are less effective (Card et al., 2018). Studies using randomized field experiments prospects (Belot et al., 2019; Altmann et al., 2022; van der Klaauw and Vethaak, 2022) find that the effects on employment, hours worked, and labor income are particularly large for unemployed job seekers in occupations with poor labor market. In contrast, Dhia et al. (2022) do not find any evidence of an impact on any employment outcome, whether in the short or medium run, while Altmann et al. (2022) find a positive effect when the share of workers exposed to the programs is low. More closely to this paper is the much less vast literature studying polices aiming at impacting the labor demand side to incentivize firms to hire in particular areas or workers from disadvantaged groups. Neumark and Grijalva (2017) examine the effects of state hiring credits, showing that specific designs—such as targeting the unemployed, enforcing job creation goals, and making credits refundable—boost job growth during recessions, though they may also induce employee churning. Also focusing on hiring credits, Cahuc et al. (2019) find significant employment gains without wage effects in France and emphasize the importance of credits being unanticipated, temporary, and targeting jobs with rigid wages for cost-effectiveness. Ku et al. (2020) instead demonstrate that payroll tax incentives can effectively stimulate local employment in regions with wage rigidity, while their removal significantly reduces local employment. McCrary (2007) studies court-ordered affirmative action hiring quotas in U.S. police departments, finding substantial changes in workforce composition but limited effects on police performance and crime outcomes. This paper contributes to the literature by examining the impact of a policy designed to stimulate local employment through increased labor demand. Unlike previous studies, this policy does not involve special incentives for hiring firms or significant direct costs for the government. Instead, it requires firms to post all job vacancies on a centralized job portal, thereby facilitating more efficient matching between job seekers and recruiters.

Secondly, we contribute to the debate between formal and informal hiring. Previous literature focused particularly on the role of networks in the labor market. The seminar paper by Montgomery (1991) provides a theoretical framework suggesting that firms rely on the social ties of productive employees to recruit high-quality workers, mitigating adverse selection problems. This theory has been recently tested by Hensvik and Skans (2016), who use coworker networks to demonstrate that firms recruit workers with better unobserved qualities, as reflected in higher draft test scores, through referrals from current employees. However, Pistaferri (1999) finds contrasting evidence, showing that while informal networks increase the likelihood of receiving job offers, they are associated with lower wages, potentially due to unobserved individual characteristics or firm-specific attributes. Extending this line of inquiry, Bayer et al. (2008)

examines geographic-based social interactions and finds strong evidence of neighborhood-based referrals improving labor market outcomes. While the previous literature fundamentally compared the two sources of hiring, to the best of our knowledge, this is the first paper performing a large scale evaluation of a policy promoting formal hiring.

Thirdly, this paper speaks to the literature studying policies regulating the hiring market. A series of papers studies how mandatory wage postings impacts employment. Frimmel et al. (2024) examines Austria's mandatory wage posting reform, which required firms to include minimum wage offers in job advertisements and finds that the reform slightly reduced the gender wage gap, primarily by increasing women's wages at the lower end of the distribution. Bamieh and Ziegler (2024) also studies this reform and finds that while it revealed a substantial gender wage gap of 15 log points, it did not lead to significant changes in gender sorting into higher-paying occupations or firms. In a different context, Škoda (2022) finds that wage transparency increased wages for newly hired workers in Slovakia, particularly in newly compliant firms, but it did not narrow the gender pay gap. A related strand of examines the impact of gender preferences in job vacancies. Kuhn and Shen (2013) develop a signaling model to explore employers' decisions to state a gender preference in job advertisements, balancing the cost of screening additional applications against the expected benefits of considering candidates from both genders. Extending this, Kuhn and Shen (2023) study the effects of a Chinese job board's policy to eliminate gender preferences from posted vacancies. They find that the change led to an increase in applications from the previously non-preferred gender group. Similarly, Card et al. (2024) provide evidence from Austria showing that prohibiting stated gender preferences in job advertisements significantly increased the share of women hired for roles traditionally targeted toward men. We contribute to this literature by studying the impact of mandatory job postings on labor market outcomes, which can be seen as the first level of transparency, allowing for all the other transparency policies to be effective.

2 Institutional Background

Following the 2014 referendum on the initiative "Against Mass Immigration", the Swiss Parliament introduced the Job Vacancy Notification Obligation (JVNO) to optimize the utilization of the domestic labor market. Under the JVNO, employers must register job vacancies in occupations with an unemployment rate meeting or exceeding a specified threshold with a regional employment agency (REA). These registered vacancies are then published on the government's online platform, "Jobroom.ch". During an initial retention period of five working days, employers are prohibited from advertising the vacancy elsewhere.[3]

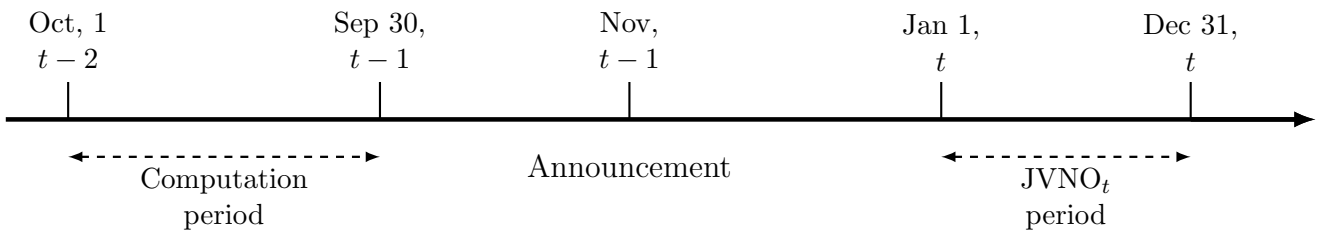
[3]The only exemptions from the JVNO consists of cases where the vacancy is filled by someone employed with the firm for at least six months, by a close relative of someone with signing authority at the firm, when the employment duration does not exceed 14 calendar days, or when the employer hires job seekers registered with the REA whose profiles are already visible on Jobroom.ch.

Within the first three working days of registration, REAs can inform employers if suitable candidates from among the unemployed are available. While employers are not obligated to interview these candidates, they must report the outcome (whether hired or not) back to the REA. Unemployed workers also benefit from direct access to Jobroom.ch, allowing them to identify and apply for roles they deem suitable during the five-day exclusivity period. This creates an information advantage for unemployed job seekers, as they are the only ones able to view and apply for these vacancies during this time.

The JVNO policy was implemented in July 2018 and has undergone six rounds up to 2023, which represents the most recent year covered in our data. As illustrated in Figure 1, each year, the Swiss State Secretariat for Economic Affairs (SECO) calculates the national unemployment rate for each occupation based on data from the period October 1 to September 30. By November, SECO announces the occupations with unemployment rates exceeding 5%, which will be subject to JVNO requirements for the following calendar year, from January 1 to December 31.

An exception to this schedule occurred during the first JVNO implementation. This initial round spanned from July 2018 to December 2019, and the unemployment rate threshold was set at 8%, rather than the standard 5% used in subsequent rounds. More importantly, the first JVNO round used a different occupational classification system, which does not align properly with the ISCO 4-digit codes used in our other data sources. Due to these discrepancies in time windows, thresholds, and, more importantly, classification systems, we exclude the first JVNO round (2018–2019) from the subsequent empirical analysis.

Figure 1: Time-schedule for JVNO policy at time t



Responsibility for monitoring and enforcing compliance with the JVNO policy lies with the Cantonal authorities. Violations of the policy are subject to fines of up to 40,000 CHF, or 20,000 CHF in cases of negligence. Compliance among employers has been high, with violations recorded in only about 1% of the inspected cases.[4]

[4]For further information on the JVNO policy, refer to SECO (2024), Ahrens et al. (2021) and Bamert et al. (2021).

3 Conceptual Framework

To understand why and how a policy mandating firms to post vacancies online could affect labor market outcomes, it is important to consider the distinction between informal and formal hiring practices. Informal hiring relies on internal staff referrals, personal networks, coaches, poaching, former employees, or recruitment consultants. This creates a relatively closed system, where those outside the firm or its network are often unaware of the vacancy. In contrast, formal hiring involves publicly posting vacancies online and selecting candidates using standardized procedures, offering a more open process accessible to anyone in the economy. Formal hiring can be more costly to firms than informal hiring, especially for small firms due to broader outreach and structured assessments, but it can yield higher-quality recruits by tapping into a larger and more diverse pool of applicants. Firms relying solely on informal hiring may face hiring inefficiencies, as they miss out on the potential quality advantages of formal hiring and might lack the knowledge or resources to implement such processes effectively.

Why and how might the JVNO policy affect labor market outcomes? Consider a framework in which firms have wage-setting power and must choose between formal and informal hiring practices.[5] This choice is influenced by the relative costs associated with each option. Assume that formal hiring practices involve higher fixed initial costs but offer lower marginal costs per hire, while, on the other hand, informal hiring practices have lower initial fixed costs but incur higher marginal costs. As a result, more productive firms are more likely to adopt formal hiring practices, advertise their vacancies, and hire more workers overall. In contrast, less productive firms typically favor informal hiring, constrained by its higher marginal costs but lower initial investment.

The introduction of the JVNO policy disrupts this equilibrium in several significant ways. By mandating formal job postings in certain occupations, the policy effectively eliminates informal hiring as an option for affected firms. It also provides additional support, such as caseworker assistance, to incentive formal hiring. Consequently, formal labor demand increases, particularly among firms switching from informal to formal hiring. At the same time, very low-productivity firms unable to bear the fixed costs of formal hiring may exit the market. This shift in hiring practices also enhances employment opportunities for less connected individuals, who benefit from the increased visibility and accessibility of formal job postings.

However, the effects of the policy on labor supply and wages are less straightforward. These outcomes depend on the interplay between the shifts in formal and informal hiring dynamics and the overall productivity distribution among firms. Although simplistic and incomplete, this conceptual framework provides

[5]For simplicity, we define formal hiring practices as those characterized by publicly posting vacancies online and informal hiring practices as those that do not involve such postings. While formal hiring typically involves more complex and standardized procedures beyond the posting itself, the distinction in this framework focuses exclusively on the use of online postings.

a basis for understanding the mechanisms through which the JVNO policy might influences labor market outcomes and sets the stage for the empirical analysis presented in the following sections.

4 Data

We rely on two primary data sources: job postings data and administrative data. The job postings data consists in the near-universe of online job postings in Switzerland scraped and assembled by a private labor market analytic firm. This job postings dataset covers the period from 2012 to 2023 for an average of almost 1 million job ads per year, and it has been shown to accurately reflect the Swiss labor market, covering approximately 91.5% of online job vacancies in Switzerland in 2017, as documented by Stellenmarkt-Monitor Schweiz (2018).[6] This dataset includes critical information such as the firm's unique identifier (UID), along with its name, the firm size, and the job location. It provides data on job occupations, classified at the 4-digit ISCO code level, the duration of job postings, the Job Ad text, and working time quotas (e.g., full-time or part-time positions). Furthermore, it includes data on the required skills, classified into more than 10,000 distinct categories.

While job postings data offers valuable insights, it has notable limitations, particularly in capturing critical aspects such as wages and job seekers characteristics. To address these gaps, job vacancy data is matched with several comprehensive administrative datasets, including Social Security Data (AVS), Population and Household Statistics (STATPOP), and the Structural Survey (SE). The AVS data provides complete records of the entire working population in Switzerland, including declared salaries for social security purposes, ensuring the complete coverage of the employed population. STATPOP, on the other hand, delivers detailed demographic and household information, covering both national and foreign residents. This data is sourced from annual censuses based on official administrative registers, offering a wide array of household and individual characteristics. Additionally, the Structural Survey (SE) enhances the dataset with granular occupational data, classified at the 4-digit ISCO code level, for approximately 3 million observations over the period 2012–2022. The integration of the administrative data sources – census data (STATPOP), social security (AVS), and structural survey (SE) – is ensured by a common individual identifier, which allows for precise matching at the individual level. Job postings data are matched with the administrative records along the three dimensions of time, occupation, and location.

The presence of administrative unique identifiers enables also the integration and enrichment of our data with supplementary administrative datasets that provide additional valuable information. Specifically, we are currently in the process of merging our database with other four other administrative datasets. First, data on job seekers including worker demographics, such as gender, nationality, age, and education

[6] For more information on the vacancy dataset and its reliability, please refer to Colella (2022), Bannert et al. (2024), and Colella et al. (2024).

attainment level, as well as previous occupation characteristics, the duration of unemployment, and job search dynamics, including the number of job applications, clicks on vacancies, etc. Second, individual-level data on the immigrant population, including employer characteristics and information on their employers. Third, data related to firm-level characteristics, contributing to a more comprehensive understanding of the labor market and job vacancies.

Overall, this richness of information enables thorough analysis and understanding the labor demand responses to the JVNO policy, not only in terms of labor demand outcomes but also in terms of its impact on employment, wages, labor supply and immigration.

5 Descriptive Statistics

Figure F1 displays the number of job postings per quarter from 2012 to 2023. Panel (a) highlights the introduction of the JVNO policy in the third quarter of 2018. The data show a steady increase in job postings over the period, with a notable decline in 2020, likely due to the COVID-19 pandemic, and a slower decline in 2023. Importantly, there are no suspicious variations around the introduction of the JVNO policy, suggesting no immediate distortions tied to its implementation. Panel (b) compares our job postings dataset with the administrative vacancy dataset, JOBSTAT, revealing a strong correlation between the two. To further validate the reliability of our job postings dataset, we examine its correlation with the number of vacancies across the most granular categories available in JOBSTAT: 13 major industry groups (approximately 1-digit NACE codes) and 7 major Swiss regions. Figures F2 display the results, with correlations exceeding 90%. These findings provide strong confidence that our job postings data accurately represent the Swiss labor market.

Figure F3 highlights the utilization of the Jobroom platform in terms of job postings and the number of firms posting. The introduction of the JVNO policy significantly increased both the number of firms using the platform to post vacancies and the number of vacancies listed.

To provide an overview of the occupations affected by the JVNO policy, Table T1 shows that 50 out of 359 ISCO 4-digit occupation codes (approximately 15%) were treated by the policy at least once during the period 2020–2023. These treated occupations accounted for about one-fourth of all job postings in Switzerland during this period. Conversely, the majority of occupations (85%) and approximately 75% of job postings were never subject to JVNO requirements.

Table T2 demonstrates that treated occupations are distributed across various major occupational groups, with a few exceptions. For instance, occupations under *Skilled Agricultural, Forestry, and Fishery Workers* were never treated by the JVNO policy. On the other hand, *Elementary Occupations* were the most

frequently treated group, with over 80% of its 4-digit codes and employment being subject to JVNO at least once. Similarly, *Service and Sales Workers* had only 15% of its 4-digit codes treated, but these accounted for over half of the employment in this major occupational group.

Figures F4 illustrate the geographical distribution of job postings and employment across Switzerland's 26 cantons, divided into octiles. Panel (a) presents the average yearly number of job postings per canton for the period 2020–2022. A large variance is observed, with Zurich leading with over 200,000 job postings per year, while smaller cantons like Appenzell Innerrhoden, Uri, and Jura have fewer than 5,000 postings annually. Panel (b) adjusts for canton size by showing the number of job postings per 100 employees. Even after normalizing, Zurich remains at the top, but smaller cantons such as Grisons and Obwalden also rank highly. Panel (c) illustrates the share of employment in each canton that is treated under the JVNO policy, based on pre-policy data (2014–2016) to avoid contamination by policy effects. The share of workers employed in occupations that would later become JVNO-treated ranges from 16% to 26%. Finally, Panel (d) shows the share of job postings in the pre-policy period (2014–2016) in each canton that correspond to JVNO-treated occupations.

6 Effects on Labor Demand outcomes

Regression Discontinuity Design Approach

To evaluate the JVNO policy's influence on labor demand, we begin with an analysis focusing on local labor market outcomes. Specifically, we investigate the effect on the number of job postings, the number of firm posting, and the level of concentration (HHI). We compute these variables aggregating the number of job postings, posting firms, and the squares of the firms' vacancy shares at the local labor market level. We define a local labor market as a combination between an occupation, identified by a ISCO 4-digit code, and a canton, Swiss NUTS level 3 geographical area. Our primary approach involves employing a regression discontinuity design approach, which consists in comparing the outcomes between occupations with an unemployment rate above the threshold with those with an unemployment rate below the threshold. Specifically, we estimate the following model:

$$\begin{aligned} Y_{rot} = \beta TR_{ot} + \gamma_1(u_{ot} - u_{0,t}) + \delta_1 TR_{ot}(u_{ot} - u_{0,t}) \\ + \gamma_2(u_{ot} - u_{0,t})^2 + \delta_2 TR_{ot}(u_{ot} - u_{0,t})^2 + \mu_o + \mu_t + \mu_r + \varepsilon_{rot} \end{aligned} \tag{1}$$

where, Y denotes the variable of interest, which is the number of job postings, the number of posting firms, or the HHI measure. $Treatment$ identifies whether the occupation o at time (year-quarter) t was affected by the JVNO policy. u_{ot} is the unemployment rate used to decide whether the occupation o at

time t is treated, and $u_{0,t}$ is the unemployment rate cut-off at time t. Finally, μ represents the fixed effects for each occupation o, canton r, and year-quarter t. The fixed effects help disentangle the effects of various observable and unobservable characteristics across regions, occupation, and time that could bias the estimates. For example, some regions or occupations are clearly larger than others, resulting in a greater number of job postings in those groups. Our preferred specification involves a quadratic fit both on the left and on the right of the cut-off because it accounts for potential non-linearity of the effect of the unemployment rate on our variables of interest. However, the results are robust even when we only consider the linear fits.

Due to the right-skewed distribution of our dependent variables, we employ an inverse hyperbolic sine (IHS) transformation to reduce the impact of outliers. The IHS transformation shares similarities with the standard logarithmic transformation, but with the crucial advantage of handling zero values.[7] This is essential for our analysis because, given the granular level of our study, some local labor markets will show no job postings or posting firms for a specific year-quarter. Applying a logarithmic transformation would exclude all these observations. However, the absence of postings in these markets is significant. One mechanism through which the JVNO policy might have worked is by incentivizing firms to move from informal to formal hiring channels. This shift would not be captured in our sample if we excluded observations with zero vacancies.

A common concern in regression discontinuity designs is the possibility of manipulation around the threshold. Specifically, individuals or entities may adjust the value of the running variable to ensure they are either treated or not. In our framework, however, this scenario is highly unlikely. Such manipulation would require either that workers are aware of the precise unemployment rate and have the ability to adjust it to exceed the 5-percentage-point cutoff, or alternatively, that the Swiss State Secretariat for Economic Affairs intentionally manipulates the unemployment rate of certain occupations to ensure they are treated. Both hypotheses are highly implausible. Other potential causes of manipulation near the margin are similarly unlikely. Nonetheless, to formally address this concern, we perform the standard McCrary density test to detect potential manipulation near the cutoff. The results, presented in Figure F5, fail to reject the null hypothesis of no manipulation around the threshold, as expected. This provides additional reassurance that manipulation is not a concern in our setting.

[7]For further information on the inverse hyperbolic transformation refer to Bellemare and Wichman (2020). We are aware of the fact that the IHS transformation may biases the results when the data have a mass of zeros (Chen and Roth, 2024), for this reason with test the results repeating the same analysis using Poisson pseudo-maximum likelihood (PPML).

Effects on Job Postings and Posting Firms

Following the Regression Discontinuity (RD) approach described in Model 1, Table 1 shows the effects of JVNO on the IHS of the number of job postings (columns 1-2), the number and the IHS of the number of posting firms (columns 3-4), and on the log HHI (columns 5-6). We can notice that JVNO has a positive and significant effect on the number of job postings and posting firms, while it has a not significant effect on the concentration measure. Independently on the quadratic or linear fit of the RD specification. Specifically, in the preferred specification (columns 2, 4, and 6) that control for a quadratic fit both above and below the cutoff, the effect of JVNO on the number of job posting and posting firms is respectively 0.17 and 0.13, which implies that the number of postings and the number of firms increases by around 18 and 13 percent.[8] The results highlight how the JVNO policy has increased the labor demand in particular both in terms of posting firms and job postings in a significant manner. The results on HHI suggests that JVNO did not impact the concentration of the job postings.

Figures F6 and F7 illustrate the relationship between the residualized number of job postings and the residualized number of firm postings around the cutoff, respectively. The outcome variables—the number of job postings and firm postings—are residualized to account for canton, occupation, and year-quarter fixed effects. The figures plot the binned averages of the residualized outcomes against the relevant JVNO unemployment rate (i.e., the running variable), with dots representing the averages and their associated 95% confidence intervals. The dotted lines depict the linear fit, while the solid curves represent the quadratic fit of the relationship between the outcome variables and the running variable. Both figures visually demonstrate a clear jump at the cutoff for the respective outcomes, providing strong evidence of a discontinuity driven by the JVNO policy.

A Shift to Formal Hiring Practices

A key feature of the JVNO policy is the requirement for firms to post job vacancies online. To investigate whether the JVNO policy was successful in encouraging firms to adopt more formal hiring practices, we compute the number of firms observed posting vacancies online for the first time. Specifically, excluding firms that had already posted at least one job vacancy in 2016 or 2017, we compute the number of distinct firms posting online for the first time for each combination of year-quarter, canton, and occupation. We create three measures of these first-time posting firms: "absolute", indicating the first time a firm posts online; "occupation", indicating the first time a firm posts in a specific occupation; and "market", indicating the first time a firm posts in a specific market, defined as the combination of a canton and an occupation.

[8] Technically, these estimates are those from a log-lin model, $(e^{\hat{\beta}} - 1) * 100$, and not for a IHS-lin model. However, it can be showed that the latter is approximately identical to the former, except in some particular cases, see Bellemare and Wichman (2020) and Chen and Roth (2024).

Table 1: Effects on labor demand outcomes

	Postings - IHS		Firms - IHS		HHI - log	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.113***	0.167***	0.091***	0.126***	-0.022	-0.022
	(0.019)	(0.019)	(0.015)	(0.013)	(0.015)	(0.018)
$(u-u_0)$ & $Tr \times (u-u_0)$	✓	✓	✓	✓	✓	✓
$(u-u_0)^2$ & $Tr \times (u-u_0)^2$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	1.88	1.88	1.55	1.55	7.88	7.88
N	164,736	164,736	164,736	164,736	97,509	97,509
R^2	0.842	0.842	0.858	0.858	0.742	0.742

Notes: This table shows the Regression Discontinuity estimates for β in equation 1. The dependent variables are the inverse hyperbolic sine transformation of the number of job postings (1-2), inverse hyperbolic sine transformation of the number of posting firms (3-4), and the logarithmic transformation of the Herfindahl-Hirschman Index (5-6). The variables are measured at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatment" is a dummy variable taking value 1 if in that year-quarter that specific occupation was treated by the JVNO policy, i.e. it had an unemployment rate above the threshold (u_0). $(u-u_0)$ & $TR \times (u-u_0)$ $(u-u_0)^2$ & $TR \times (u-u_0)^2$ denote respectively the linear and quadratic fit of the RDD. All specifications includes Canton, Year-quarter, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: Job Postings dataset, period 2020-2023. *p < 0.10, **p < 0.05, ***p < 0.01.

Using these measures as dependent variables, we estimate the effects using the same RD specification as in Model 1. Table 2 presents the estimates. Focusing on the even-numbered columns, which control for a quadratic fit above and below the cutoff, we find that the JVNO treatment significantly increases the number of firms starting to post their vacancies online. Specifically, being treated by JVNO increases the number of firms posting for the first time in "absolute" terms by approximately 5 percent, in "occupation" terms by 12 percent, and in "market" terms by 10 percent. These results highlight how the JVNO policy successfully encourages firms to adopt more formal hiring practices, shifting them from informal recruitment channels to the more formal practice of posting job vacancies online.

Given that JVNO mandates firms to post their vacancies on the governmental portal *Jobroom.ch*, the observed effect could partly be mechanical, as firms comply with the policy requirement without necessarily reflecting a broader shift toward more formal hiring practices. To examine this, we investigate whether the policy's impact is confined solely to *Jobroom.ch*, where firms are required to post, or whether it also generates spillover effects, encouraging firms to post vacancies on other online platforms beyond *Jobroom.ch*. Table 3 estimates the effect of JVNO on the inverse hyperbolic sine (IHS) of the number of job postings and firm postings across three categories: Total, postings on *Jobroom.ch*, and postings on other online platforms.

Table 2: Increase in First-time Posting Firms

	Absolute		Occupation		Market	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.054***	0.044***	0.086***	0.120***	0.082***	0.108***
	(0.015)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)
$(u-u_0)$ & $Tr \times (u-u_0)$	✓	✓	✓	✓	✓	✓
$(u-u_0)^2$ & $Tr \times (u-u_0)^2$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	.322	.322	.849	.849	1.01	1.01
N	164,736	164,736	164,736	164,736	164,736	164,736
R^2	0.556	0.556	0.728	0.728	0.791	0.791

Notes: This table shows the Regression Discontinuity estimates for β in equation 1. The dependent variables are the inverse hyperbolic sine transformation of the number of distinct firms that post online for the first time in the periods (2016-2017, 2020-2022) in absolute (columns 1-2), in that specific occupation (3-4), and in that specific market (5-6). All the dependent variables are aggregated at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatment" is a dummy variable taking value 1 if in that year-quarter that specific occupation was treated by the JVNO policy, i.e. it had an unemployment rate above the threshold (u_0). $(u-u_0)$ & $TR \times (u-u_0)$ $(u-u_0)^2$ & $TR \times (u-u_0)^2$ denote respectively the linear and quadratic fit of the RDD. All specifications includes Canton, Year-quarter, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: Job Postings dataset, period 2020-2023, considering firms that did not post job posting in the period 2016-2017. *p < 0.10, **p < 0.05, ***p < 0.01.

The results indicate that while the strongest effects of JVNO occur through the Jobroom portal—with an increase of around 30 percent in both the number of job postings and posting firms—it also significantly increases posting on other online platforms. Specifically, Table 3 shows an increase of approximately 12 percent in the number of job postings and about 5 percent in the number of posting firms on platforms other than Jobroom. These findings suggest that the JVNO policy not only enforces compliance but also stimulates a broader adoption of formal hiring practices across multiple online recruitment channels.

Robustness checks

In this section, we present further evidence corroborating the robustness of the positive effect of JVNO on the labor demand outcomes. First, we show that our findings are robust to considering different bandwidths in the regression discontinuity design. Second, we control for potential bias from the use of the inverse hyperbolic sine transformation running a Poisson pseudo-maximum likelihood (PPML) given the presence of a mass of zero in our outcome variables (Chen and Roth, 2024). Third, we control for the potential biased induced by a regression to the mean. Given that the occupations are treated if they observed a high level of unemployment, it can be that be reverting back to the mean the positive effect we observe

Table 3: More Postings and more Firms outside Jobroom

Dependent Variable:	*Postings - IHS*			*Firms - IHS*		
	Total	Jobroom	Not Jobroom	Total	Jobroom	Not Jobroom
Treatment	0.167***	0.295***	0.115***	0.126***	0.253***	0.052***
	(0.019)	(0.036)	(0.020)	(0.013)	(0.030)	(0.011)
$(u-u_0)$ & Tr $\times$ $(u-u_0)$	✓	✓	✓	✓	✓	✓
$(u-u_0)^2$ & Tr $\times$ $(u-u_0)^2$	✓	✓	✓	✓	✓	✓
Canton FE	✓	✓	✓	✓	✓	✓
Year $\times$ Quarter FE	✓	✓	✓	✓	✓	✓
Occupation (ISCO4) FE	✓	✓	✓	✓	✓	✓
MDV	1.88	.53	1.8	1.55	.476	1.46
N	164,736	164,736	164,736	164,736	164,736	164,736
R^2	0.842	0.620	0.838	0.858	0.636	0.853

Notes: This table shows the Regression Discontinuity estimates for β in equation 1. The first three columns have as dependent variables the inverse hyperbolic sine transformation of the number of job postings in total (1), in the Jobroom platform (2), and outside the Jobroom platform (3). The last three columns have as dependent variables the inverse hyperbolic sine transformation of the number of firms posting in total (1), in the Jobroom platform (2), and outside the Jobroom platform (3). All the dependent variables are computed at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatment" is a dummy variable taking value 1 if in that year-quarter that specific occupation was treated by the JVNO policy, i.e. it had an unemployment rate above the threshold (u_0). $(u-u_0)$ & $TR \times (u-u_0)$ $(u-u_0)^2$ & $TR \times (u-u_0)^2$ denote respectively the linear and quadratic fit of the RDD. All specifications includes Canton, Year-quarter, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: Job Postings dataset, period 2020-2023. *p < 0.10, **p < 0.05, ***p < 0.01.

is driven by this reversion to the mean rather than by the policy itself. Fourth, we perform some placebo test, imputing the treatment to occupations in the pre-treatment period. Fifth, we test the sensitivity of our estimates following the RD estimations procedures in Calonico et al. (2014) and Armstrong and Kolesár (2018). Sixth, we investigate whether the results are coming from employers trying to circumvent the policy by posting vacancies of no treated occupations to closely related treated occupations.

Varying Bandwidths

The Regression Discontinuity Design (RDD) compares outcomes for occupations on either side of the unemployment threshold. However, occupations far above or far below the threshold, even after controlling for linear and quadratic fits, may not be fully comparable. Occupations far above the threshold are characterized by a relatively high unemployment rate in the previous year, which could be driven by occupation-specific, time-varying shocks. These shocks cannot be fully ruled out by controlling for occupation fixed effects or by including linear and quadratic fits of the unemployment rate effect. As a result, the estimates could reflect the influence of these time-varying shocks rather than the true effect of the policy.

To address this potential threat to our identification strategy, we implement the same RDD described in

Equation 1, restricting the analysis to occupations within varying bandwidths around the cutoff. Due to the reduction in the number of observations caused by this restriction, we include only a linear fit to avoid overfitting. Nevertheless, the results remain robust when a quadratic fit is included.

Table T3 displays the results. Columns (1–4) report the estimates for the inverse hyperbolic sine (IHS) of the number of job postings, while Columns (5–8) present the results for the IHS of the number of posting firms. Columns (1) and (4) use a bandwidth of ± 1 percentage point, Columns (2) and (5) a bandwidth of ± 2 percentage points, and Columns (3) and (6) a bandwidth of ± 3 percentage points. Across all specifications, the estimates show a positive and statistically significant effect of the JVNO policy on both the IHS of job postings and posting firms. Moreover, as expected in an RDD framework, the estimated effects decrease as the bandwidth widens. This is consistent with the notion that occupations further from the cutoff are less comparable.

Poisson Pseudo-Maximum Likelihood estimation

The presence of a mass of zeros in our outcome variables can bias our IHS estimates (Chen and Roth, 2024). To test the relevance of this potential threat, we reproduce Table 1 substituting the IHS transformation with a Poisson Pseudo-Maximum Likelihood (PPML) estimation on the number of job postings and firm postings. Table T4 reports the results. The estimates are in line with what obtained using the inverse hyperbolic sine transformation, highlighting how the mass of zeros does not constitute a significant issue in our estimation. The only smaller difference is on the effect of the posting firms, which although still having a positive statistically significant estimates, its magnitude shrinks. The number of posting firms in the PPML model increases by around 7 percent rather than the 13 percent increase obtained with the estimation using the inverse hyperbolic sine transformation.

Permutation test: mean reversion

Another potential concern in this estimation is the possibility of a reversion-to-the-mean effect. Occupations treated by JVNO exhibit relatively high unemployment rates, by construction, raising the likelihood that following a particularly negative shock, a positive shock may subsides in the following year. If this were the case, the observed positive effect of JVNO might be misleading, reflecting this natural reversion to the mean rather than the true impact of the policy.

To address this concern, we conduct a permutation test. Specifically, we replicate the regression analysis using arbitrary unemployment rate thresholds as cutoffs, varying them in 0.1 percentage point increments from 1 to 4 percentage points and from 6.5 to 8 percentage points. If the observed effects were driven by mean reversion, we would expect similar results across these arbitrary cutoffs. The results of the test on

the job postings are presented in Figure F8 and on the posting firms in Figure F9. The figures document that the estimates at the actual cutoff are statistically significant and clearly distinct from the estimates at the incorrect cutoffs. In contrast, the estimates at the incorrect cutoffs are distributed around zero, supporting the conclusion that the observed effects are attributable to the JVNO policy rather than to a mean reversion phenomenon.

Placebo

Table T5 provides a placebo check, confirming that there are no jumps in job postings, firm postings, or HHI concentration in years when the JVNO policy was not yet active. Specifically, we anticipate the JVNO policy to the years 2016 and 2017, assigning the treatment status to occupations with unemployment rate above the 5 percentage points threshold in the previous year. None of the estimates are statistically significant at the 5 percent confidence level. These results suggest a minimal likelihood that the observed effects are due to random fluctuations or chance. Instead, the findings provide strong support that the detected effects are indeed driven by the variation introduced through the implementation of the JVNO policy.

RD-robust and RD-honest

We estimate the first and second-degree polynomials for the optimal bandwidth calculated using the non-parametric procedure from Calonico et al. (2014). Our coefficient of interest β measures the effect of JVNO treatment on the inverse hyperbolic sine transformation of the number of job postings and the number of firms posting. We choose a specification with canton, year-quarter, and occupation fixed-effects as our main one for several reasons. First, since treatment and control occupations have similar frequency across cantons, we can increase the efficiency of our estimates without biasing them when adding fixed-effects (Calonico et al., 2019). Second, as cantons are particularly diverse and have particular autonomy in enforcing the policy as well as different regional employment agency, we compare cells subject to the same canton-level regulation. Third, controlling for occupation fixed effect can remove the idiosyncratic differences between each other in term of job postings and number of firms. Table T6 display the results. Independently of the specification, the estimates are in line with our main specification corroborating the positive effect of JVNO on both the number of job postings and firm postings. Specifically, the effects are even larger in magnitude.

Posting firms manipulating the occupation choice

Occupations defined by 4-digit ISCO codes are highly specific, and many occupations within this classification can be considered quite similar. This specificity raises the possibility that firms could evade or strategically adjust their participation in the JVNO policy by slightly altering how they classify the occupations for which they are hiring. For instance, firms might misclassify a job's occupation to either comply with or avoid the policy requirements. To account for this potential manipulation by employers, we examine the effects of the policy on occupations that are not directly treated but belong to the same 3-digit ISCO category as at least one treated 4-digit occupation. This approach allows us to identify any spillover effects or strategic reclassification within closely related occupations. Table T7 presents the results of this analysis. We find no statistically significant effects of the policy on job postings, firm postings, or the HHI concentration measure for these related occupations. This suggests that employer manipulation or spillover effects at the level of related occupations are unlikely to play a meaningful role in our findings.

7 Effects on Employment and Earnings

In the previous sections, we documented how the JVNO policy positively affected labor demand, both in terms of job postings and firm postings. In this section, we examine whether the JVNO policy also influenced employment and earnings.

To investigate the effect of JVNO on employment and earnings, we match data from the Structural Survey (SE) with Social Security records (AVS). By integrating Social Security information into the Structural Survey, we gain detailed data on close to 1 million individuals surveyed by the SE in the period 2020–2022. This combined dataset provides insights into individuals' employment status, occupation, and earnings. We aggregate this information at the level of canton, occupation (4-digit ISCO code), and year. Using the same model specification as in Model 1, which was employed to analyze labor demand outcomes, we examine the effect of the JVNO policy on the number of employed workers and their average monthly earnings. Note that we use annual data rather than year-quarter data because the SE reports information on a yearly basis.[9] Table 4 presents the results.

Column (1) reports the results for the IHS number of employed workers in each canton, year, and occupation (4-digit ISCO), while Columns (2) and (3) present respectively the IHS number of female and Non Swiss employed workers. Column (4) displays the IHS. annual earnings for work declared to Social Security during the year, divided by the number of months the individuals were employed that year. All the outcomes are positive, suggesting that the JVNO policy has a beneficial impact on employment and earnings. However,

[9]We are also losing one year (2023) with regards to the analysis on the Job Postings dataset, because at the moment we do not have access to the SE data for the year 2023, but we are planning to get it.

Table 4: RD estimates: Employment and Earnings

	Employment			*Earnings*
	Total	Female	Non Swiss	Monthly average
	(1)	(2)	(3)	(4)
Treatment	0.086**	0.097	0.160	0.001
	(0.034)	(0.127)	(0.152)	(0.045)
$(u-u_0)$ & Tr $\times$ $(u-u_0)$	✓	✓	✓	✓
$(u-u_0)^2$ & Tr $\times$ $(u-u_0)^2$	✓	✓	✓	✓
Canton FE	✓	✓	✓	✓
Year	✓	✓	✓	✓
Occupation (ISCO4) FE	✓	✓	✓	✓
MDV	5.84	3.89	0.98	8.51
N	20,370	20,370	20,370	19,728
R^2	0.802	0.679	0.388	0.547

Notes: This table shows the RD of the effect of JVNO on the IHS. number of employed workers (1), IHS. number of female employed workers (2), IHS. number of non Swiss employed workers (3), and on the IHS. average monthly earnings (4). All the dependent variables are computed at the combination between an occupation (4-digit ISCO), a Canton, and a year. The independent variable "Treatment" is a dummy variable taking value 1 if in that year that specific occupation was treated by the JVNO policy, i.e. it had an unemployment rate above the threshold (u_0). $(u-u_0)$ & $TR \times (u-u_0)$ $(u-u_0)^2$ & $TR \times (u-u_0)^2$ denote respectively the linear and quadratic fit of the RDD. All specifications includes Canton, Year, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: merged AVS and SE data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

only the estimate in Column (1) is statistically significant at the 5 percent confidence level. The estimated coefficient of 0.086 indicates that employment in JVNO-treated occupations increases by approximately 9 percent. It is important to note that, in contrast to the analysis on job postings, this analysis relies on a sample of approximately 300,000 individuals per year. As a result, it may not fully represent the entire population. Nonetheless, the observed positive effect is promising.

An additional potential concern in this estimation is the possibility of a reversion-to-the-mean phenomenon. Since the occupations treated by JVNO tend to have relatively high unemployment rates, it is possible that after experiencing a particularly negative shock that qualifies an occupation for treatment, the following year sees a natural reversion to its mean. If this were the case, the observed positive effect of JVNO could be spurious, driven by this mean reversion rather than the policy itself. To address this concern, we perform a permutation test. Specifically, we repeat the regression analysis, assigning cutoffs to arbitrary unemployment rate thresholds in 0.1 percentage point increments from 1 to 4 percentage points, and from 6.5 to 8 percentage points. If the observed results were due to mean reversion, we would expect similar results across these alternative incorrect cutoffs. The results of this test are presented in Figure F10. The figure shows that the estimate at the actual cutoff is statistically significant and distinct from the

estimates at the incorrect cutoffs. The estimates at the incorrect cutoffs are instead distributed around zero, consistent with the hypothesis that the observed effects are attributable to the JVNO policy rather than reversion to the mean.

8 Total Effects: Commuting Zones analysis

A key challenge in evaluating the impact of the JVNO policy is determining whether the observed labor demand and employment effects derive from a genuine increase on the labor demand and on the employment or if they are merely shifts in labor between occupations. The RD design compares occupations close to the cutoff, which have a similar unemployment rate, therefore, the estimates are in relative term with respect to those occupations that are close below the cutoff. Therefore, employment effect might be driven by shifts across occupation rather than a genuine increase. To address this, we analyze the JVNO impact at the labor market level by examining aggregate employment outcomes. Since comparing treated and non-treated regions is not feasible in this context, we focus on exposure to the policy at the commuting zone level. This approach helps disentangle substitution effects from true employment gains, providing a more comprehensive understanding of the policy's implications.

Exposure Measure

By matching the Structural Survey (SE) with the Administrative Census (STATPOP), we constructed the share of workers employed in each occupation within each of the 101 commuting zones in Switzerland during the pre-policy period (2014–2016), ensuring so that these shares are unaffected by the JVNO policy. Using this pre-policy occupational distribution, we then constructed an Exposure measure for each commuting zone and year. This measure is calculated as the sum of the products between the share of workers in each occupation and an indicator variable that identifies whether the occupation was treated by the JVNO policy in that year. Specifically,

$$Exposure_{it} = \sum_{o} share_{io(2014-2016)} \times Treatment_{ot} \tag{2}$$

$$share_{io(2014-2016)} = \frac{Employment_{io(2014-2016)}}{\sum_o Employment_{io(2014-2016)}}$$

After constructing the *Exposure* measure for each commuting zone during the period 2020–2022, we investigate whether commuting zones with a relatively higher share of treated workers, indicating greater exposure to the policy, experience a stronger effect on employment outcomes. Formally, we estimate the

following model:

$$Y_{it} = \alpha + \beta StdExposure_{it} + \mu_i + \mu_t + \varepsilon_{it} \tag{3}$$

where Y_{it} is the outcome of interest for the commuting zone i at time t. μ_i and μ_t are respectively the commuting zone and year fixed effects. $StdExposure_{it}$ is the standardized value of the Exposure measure defined in Equation 2, such that an increase of 1 unit of the $StdExposure$ implies an increase of 1 standard deviation of this measure.[10]

Figure F11 shows the distribution of the *Exposure* measure across commuting zones and years. *Exposure* ranges from 4 percentage points to 45 percentage points, with a mode around 14 percentage points and an average of 15 percentage points, exhibiting a longer right tail. Figure F12 illustrates the geographical distribution of the average *Exposure* across the period 2020–2022. A noticeable variation emerges across different commuting zones, with a higher proportion in the southern regions, except for the commuting zones in the Ticino canton.

Results

Using the Social Security Data, we construct, for each commuting zone and year, the number of employed individuals aged 20 to 65, disaggregated by various demographic characteristics such as sex and citizenship. Additionally, we calculate average monthly earnings, defined as total declared earnings from dependent employment in a given year divided by the number of months individuals were employed.

For citizenship, we categorize non-Swiss individuals into three groups: new arrivals, recent arrivals, and long-term residents. New arrivals are defined as non-Swiss individuals who arrived in Switzerland during the current year; recent arrivals are those who arrived more than one year but less than ten years ago; and long-term residents are individuals who have been in Switzerland for more than ten years.

Since the JVNO policy restricts the inflow of new non-Swiss workers, we further investigate whether commuting zones closer to the border—those more directly affected by cross-border labor inflows—experience stronger impacts from the policy. Bordering commuting zones are defined as those where the average distance from all municipalities within the zone to the national border is less than 20 kilometers. These zones account for 46 percent of all commuting zones, or 46 out of 101.

As a preview of the results, we find a positive and statistically significant effect of *Exposure* on employment, with an increase of approximately 8 percent, consistent with the estimates reported in Table 4. Notably,

[10] Formally, $StdExposure_{it} = \frac{Exposure_{it} - \overline{Exposure}}{\sigma_{Exposure}}$, where $\overline{Exposure}$ is the average exposure level in our sample, and $\sigma_{Exposure}$ is its variance.

Table 5: Exposure effect on Employment and Earnings by Sex

	Employment			Earnings		
	Total	Male	Female	Total	Male	Female
Exposure	0.080***	0.079***	0.080***	0.006*	0.002	0.013***
	(0.022)	(0.021)	(0.022)	(0.003)	(0.004)	(0.003)
CZ	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
MDV	10.1	9.52	9.39	8.66	8.86	8.37
N	303	303	303	303	303	303
R^2	0.997	0.997	0.997	0.998	0.997	0.997

Notes: This table shows the effect of JVNO exposure measure on the Log. number of employed workers (1-3) and on the Log. average monthly earnings (4-6). All the dependent variables are computed at the combination between a commuting zone and a year, considering all the individuals between 20 and 65 years old. In the columns Male and Female the dependent variable is computed considering only Male and Female individuals, respectively. The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

the effect on employment is stronger for new arrivals. Regarding earnings, the policy's impact is more pronounced among females and long-term non-Swiss workers. Furthermore, the effect of *Exposure* is stronger in commuting zones located closer to the Swiss border.

Employment and Earnings by Sex

Table 5 presents the estimates of the effect of the standardized commuting-zone-level *Exposure* measure on employment and earnings, disaggregated by sex. Column (1) reports the effect on the log number of employed individuals per commuting zone in total, while Column (2) provides the same estimate for Males, and Column (3) for Females. Columns (4–6) display the effects on the log of monthly average earnings, similarly divided by sex. All specifications include both commuting zone and year fixed effects. The point estimates for employment indicate an increase of approximately 8 percentage points, suggesting that a one-standard-deviation increase in the *Exposure* measure leads to an 8 percent rise in employment.[11] Importantly, there is no statistically significant difference in the effect between males and females. In terms of earnings, the results show no statistically significant effect for males, but a positive and statistically significant effect for females. Specifically, a one-standard-deviation increase in the *Exposure* measure corresponds to an approximately 1 percent increase in average monthly employment earnings for females.

[11]Figure F13 shows the binned scatter plot of the effect of the standardized exposure on the log. number of employed workers in that commuting zone, both the axes are residualized for the fixed effects per year and commuting zone.

Employment and Earnings by Nationality

Table 6 presents the estimates of the effect of the standardized commuting-zone-level *Exposure* measure on log employment, disaggregated by nationality and years since arrival in Switzerland. Column (1) reports the effect on the log number of employed individuals per commuting zone overall, while Column (2) provides the estimate for Swiss nationals, and Column (3) for non-Swiss individuals, regardless of their year of arrival in Switzerland. Columns (4–6) further refine the analysis for non-Swiss individuals, showing the effects for those who arrived in Switzerland within the year (Column 4), between 2 and 10 years ago (Column 5), and more than 10 years ago (Column 6). All specifications include both commuting zone and year fixed effects.

The point estimates for employment indicate an increase of approximately 14 percentage points for non-Swiss workers, suggesting that a one-standard-deviation increase in the *Exposure* measure leads to a 14 percent rise in employment for this group. Notably, the effect is primarily driven by new arrivals to Switzerland, whose employment increases by around 18 percent.

Table T8 provides the estimates of the effect of the *Exposure* measure on log average monthly earnings, also disaggregated by nationality and years since arrival in Switzerland. In contrast to the results for employment, the effects on earnings are relatively modest. Swiss workers experience an average increase of approximately 1 percent, while non-recent non-Swiss workers see increases ranging from 1 to 4 percent in their average monthly earnings.

The differing patterns of results for years since arrival with respect to employment and earnings suggest a nuanced impact of the policy. Recent immigrants appear to benefit primarily from increased visibility of potential job opportunities, which drives their employment gains. In contrast, less recent immigrants likely benefit from an expanded pool of job opportunities that are more comparable to those available to Swiss nationals, enabling them to improve their employment situations and earnings.

Employment and Earnings, effect in Bordering commuting zones

Table T9 replicates Table 6, introducing an interaction term between the standardized *Exposure* measure and a dummy variable indicating whether the commuting zone is a bordering zone. A bordering commuting zone is defined as one where the average distance from all its composing municipalities to the national border is less than 20 kilometers. As expected, the effect is stronger for commuting zones near the border, which are more commonly associated with employing new immigrants and are most affected by policies that limit or postpone the inflow of new immigrants. Interestingly, the positive impact observed for the employment of less recent immigrants suggests a degree of substitutability between new and old immigrants in the labor market. However, the lack of a statistically significant negative effect on the employment of

Table 6: Exposure effect on Employment by Nationality

		Nationality		Non Swiss, arrival date		
	Total	Swiss	Non Swiss	<1 year	2-10 years	>10 years
Exposure	0.080***	0.038*	0.144***	0.183***	0.099***	0.049**
	(0.022)	(0.020)	(0.028)	(0.052)	(0.028)	(0.022)
CZ	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
MDV	10.1	9.82	8.79	6.19	7.88	8.07
N	303	303	303	303	303	303
R^2	0.997	0.997	0.996	0.984	0.996	0.998

Notes: This table shows the effect of JVNO exposure measure on the Log. number of employed workers disaggregated by nationality. All the dependent variables are computed at the combination between a commuting zone and a year, considering all the individuals between 20 and 65 years old. In the columns Swiss and Non Swiss the dependent variable is computed considering only Swiss and Non Swiss individuals, respectively. Finally, the last three columns computed the log number of employed non Swiss individuals that arrived in Switzerland that year ($< 1 year$), between 2 and 10 years ago ($2 - 10 years$) and more than 10 years ago ($> 10 years$). The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

new immigrants appears to contradict this hypothesis, pointing to the need for further investigation to clarify this dynamic.

Population Composition

The observed rise in the number of employed workers may be driven by an overall increase in population rather than higher employment rates. To assess whether this growth in employment is not primarily due to population expansion, we examine the impact of exposure on the demographic composition of the affected commuting zones.

Table T10 presents the effects of the standardized exposure measure on the log number of individuals in various categories. Column (1) shows the effect on the log number of all individuals aged 20 to 65 within the commuting zone for that year. Columns (2) and (3) report the effects on the log number of Swiss and non-Swiss individuals, respectively. Finally, Columns (4) through (6) break down the effects for non-Swiss individuals based on their year of arrival in Switzerland.

An increase of one standard deviation in exposure leads to an approximate 8 percent rise in the population within the commuting zone. This effect is primarily driven by the growth of the non-Swiss population, which increases by about 14 percent. Among non-Swiss individuals, the most affected group consists of

Table 7: Exposure effect on Employment share by Nationality

		Nationality		Non Swiss, arrival date		
	Total	Swiss	Non Swiss	<1 year	2-10 years	>10 years
Exposure	0.210**	-0.199**	0.320	4.212***	-1.034**	-0.670***
	(0.098)	(0.084)	(0.287)	(1.158)	(0.412)	(0.255)
CZ	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
MDV	78.2	79.4	75.1	57.8	75.9	77.7
N	303	303	303	303	303	303
R^2	0.998	0.998	0.987	0.951	0.976	0.988

Notes: This table shows the effect of JVNO exposure measure on the share of individuals by nationality that are employed. All the dependent variables are computed at the combination between a commuting zone and a year, considering all the individuals between 20 and 65 years old. In the columns Swiss and Non Swiss the dependent variable is computed considering only Swiss and Non Swiss individuals, respectively. Finally, the last three columns computed the employment share of non Swiss individuals that arrived in Switzerland that year ($< 1year$), between 2 and 10 years ago ($2 - 10years$) and more than 10 years ago ($> 10years$). The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

recent immigrants, those who arrived in Switzerland between two and ten years prior, who experience an 11 percent increase. However, the effect on new arrivals (Column 4) is not statistically significant. Table T11 reports the effects on the population share of each group relative to the total population in the commuting zone. A one-standard-deviation increase in the exposure measure raises the share of non-Swiss individuals by approximately 2 percentage points, with nearly all of this increase attributable to new immigrants who arrived in Switzerland that same year.

Given the concurrent increases in both population and employment, we further investigate by examining employment rates within each population group. Table 7 reports the results, regressing employment rates (in percentage terms) for each category on the exposure measure. Column (1) shows that a one-standard-deviation increase in exposure raises the overall employment rate in the commuting zone by 0.2 percentage points. However, the employment rate for Swiss individuals declines by about 0.2 percentage points. Similarly, the employment rate for recent and long-term non-Swiss residents, those who have lived in Switzerland for at least two years, decreases by roughly 1 percentage point. By contrast, the employment rate for new immigrants, those who arrived in Switzerland that year, increases by more than 4 percentage points, which consists in an increase of more than 7 percent.

Placebo check

To provide further evidence that the effect is the result of the JVNO policy and is not due to any confounding trend, Table T12 provides a placebo check. We falsely retro dated the exposure measure by three years. Imputing the exposure measure for that commuting zone three years before. We the replicate the same results as in Table 6 in the period 2017-2019. We can notice that there is no statistical significant effects for Swiss and non Swiss employment, with the exception of the effects of non new immigrants.

9 Conclusion

In this paper, we analyze the impact of a policy mandating firms to post job vacancies online on labor market outcomes. Specifically, we study the Swiss Job Vacancy Notification Obligation (JVNO), a policy introduced to improve job search outcomes by requiring employers in specific high-unemployment occupations to advertise vacancies on the governmental platform *Jobroom.ch*. By leveraging rich administrative and web-scraped job postings data and combining a regression discontinuity design with spatial analyses across commuting zones, we provide new evidence on the effects of mandating formal hiring practices.

Our findings document several key insights. First, the JVNO policy significantly increased the number of job postings and firms participating in formal hiring channels, with increases of approximately 17 percent and 13 percent, respectively, at the policy threshold. This effect extended beyond *Jobroom.ch*, suggesting positive spillovers on other online job platforms. A substantial share of this growth was driven by firms posting vacancies online for the first time, highlighting the policy's role in fostering adoption of formal hiring practices among firms previously reliant on informal methods.

Second, we show that the policy led to genuine job creation, with employment in JVNO-treated occupations increasing by approximately 9 percent. This addresses concerns that the policy's observed effects could be driven solely by a reclassification of hiring practices.

Third, we extend the analysis to the commuting-zone level, examining aggregate labor market outcomes and migration. Commuting zones with higher exposure to JVNO-treated occupations experienced significant employment gains without negative effects on earnings. Employment effects were particularly pronounced for non-Swiss workers, especially recent arrivals.

This paper contributes to the literature on labor market policies by providing the first large-scale evaluation of a mandate targeting formal hiring practices. Our results highlight the potential for such policies to increase transparency and inclusivity in the labor market, particularly for disadvantaged groups, while also fostering compliance with hiring standards. More broadly, our findings underscore the importance of demand-side interventions in addressing labor market inefficiencies, complementing traditional supply-side

policies like job search assistance and training programs.

The implications of this study are twofold. First, policies that encourage formal hiring can mitigate barriers faced by less-connected workers, enhancing equity in access to job opportunities. Second, mandates like JVNO can shape firms' hiring behaviors, encouraging broader adoption of transparent and regulated practices.

References

Ahrens, A., P. Arni, D. Hangartner, R. Lalive, T. Lehmann, and J. Pianzola (2021): "Wirkungsevaluation der Stellenmeldepflicht I," *Grundlagen für die Wirtschaftspolitik Nr. 21. Staatssekretariat für Wirtschaft SECO, Bern.*

Algan, Y., B. Crépon, and D. Glover (2020): "Are active labor market policies directed at firms effective? Evidence from a randomized evaluation with local employment agencies," *J-PAL working paper.*

Altmann, S., A. Glenny, R. Mahlstedt, and A. Sebald (2022): "The direct and indirect effects of online job search advice," .

Armstrong, T. B. and M. Kolesár (2018): "Optimal inference in a class of regression models," *Econometrica*, 86, 655–683.

Bamert, J., A. Beerli, B. Kaiser, D. Kopp, and M. Siegenthaler (2021): "Monitoringevaluation der Stellenmeldepflicht I," *Grundlagen für die Wirtschaftspolitik Nr. 19. Staatssekretariat für Wirtschaft SECO, Bern.*

Bamieh, O. and L. Ziegler (2024): "Can wage transparency alleviate gender sorting in the labor market?" *Economic Policy*, eiae025.

Bannert, M., J. Klaeui, D. Kopp, M. Siegenthaler, S. Thöni, and J. Winkelmann (2024): "Swiss Job Tracker: New Weekly Indices of Online Job Postings in Switzerland," *Technical Report.*

Bartik, T. J. (2001): "Jobs for the poor: Can labor demand policies help?" .

Bayer, P., S. L. Ross, and G. Topa (2008): "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes," *Journal of Political Economy*, 116, 1150–1196.

Bellemare, M. F. and C. J. Wichman (2020): "Elasticities and the inverse hyperbolic sine transformation," *Oxford Bulletin of Economics and Statistics*, 82, 50–61.

Belot, M., P. Kircher, and P. Muller (2019): "Providing advice to jobseekers at low cost: An experimental study on online advice," *The review of economic studies*, 86, 1411–1447.

Bolhaar, J., N. Ketel, and B. van der Klaauw (2020): "Caseworker's discretion and the effectiveness of welfare-to-work programs," *Journal of Public Economics*, 183, 104080.

Cahuc, P., S. Carcillo, and T. Le Barbanchon (2019): "The effectiveness of hiring credits," *The Review of Economic Studies*, 86, 593–626.

Caliendo, M. and R. Schmidl (2016): "Youth unemployment and active labor market policies in Europe," *IZA Journal of Labor Policy*, 5, 1–30.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik (2019): "Regression discontinuity designs using covariates," *Review of Economics and Statistics*, 101, 442–451.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014): "Robust nonparametric confidence intervals for regression-discontinuity designs," *Econometrica*, 82, 2295–2326.

Card, D., F. Colella, and R. Lalive (2024): "Gender preferences in job vacancies and workplace gender diversity," *Review of Economic Studies*, rdae085.

Card, D., J. Kluve, and A. Weber (2018): "What works? A meta analysis of recent active labor market program evaluations," *Journal of the European Economic Association*, 16, 894–931.

Chen, J. and J. Roth (2024): "Logs with zeros? Some problems and solutions," *The Quarterly Journal of Economics*, 139, 891–936.

Colella, F. (2022): "The Effect of Trade on Skill Requirements: Evidence from Job Postings," *Mimeo*.

Colella, F., R. Lalive, and A. Marcato (2024): "The Geography of Labor Demand in Switzerland," *Mimeo*.

Dhia, A. B., B. Crépon, E. Mbih, L. Paul-Delvaux, B. Picard, and V. Pons (2022): "Can a website bring unemployment down? Experimental evidence from France," *NBER, Working paper*.

Frimmel, W., B. Schmidpeter, R. Wiesinger, and R. Winter-Ebmer (2024): "External pay transparency and the gender wage gap," Tech. rep., RF Berlin-CReAM Discussion Paper Series.

Hensvik, L. and O. N. Skans (2016): "Social networks, employee selection, and labor market outcomes," *Journal of Labor Economics*, 34, 825–867.

Kluve, J., S. Puerto, D. Robalino, J. M. Romero, F. Rother, J. Stöterau, F. Weidenkaff, and M. Witte (2019): "Do youth employment programs improve labor market outcomes? A quantitative review," *World Development*, 114, 237–253.

Ku, H., U. Schönberg, and R. C. Schreiner (2020): "Do place-based tax incentives create jobs?" *Journal of Public Economics*, 191, 104105.

Kuhn, P. and K. Shen (2013): "Gender discrimination in job ads: Evidence from china," *The Quarterly Journal of Economics*, 128, 287–336.

——— (2023): "What happens when employers can no longer discriminate in job ads?" *American Economic Review*, 113, 1013–1048.

Lalive, R., J. C. Van Ours, and J. Zweimüller (2008): "The impact of active labour market programmes on the duration of unemployment in Switzerland," *The Economic Journal*, 118, 235–257.

Le Barbanchon, T., L. Hensvik, and R. Rathelot (2023): "How can AI improve search and matching? Evidence from 59 million personalized job recommendations," Tech. rep., Working Paper.

McCrary, J. (2007): "The effect of court-ordered hiring quotas on the composition and quality of police," *American Economic Review*, 97, 318–353.

Modestino, A. S., D. Shoag, and J. Ballance (2020): "Upskilling: Do employers demand greater skill when workers are plentiful?" *Review of Economics and Statistics*, 102, 793–805.

Montgomery, J. D. (1991): "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis," *The American Economic Review*, 81, 1408–1418.

Neumark, D. and D. Grijalva (2017): "The employment effects of state hiring credits," *ILR Review*, 70, 1111–1145.

Pistaferri, L. (1999): "INFORMAL NETWORKS IN THE ITALIAN LABOR MARKET," *Giornale degli Economisti e Annali di Economia*, 58 (Anno 112), 355–375.

SECO (2024): "Vollzugsmonitoring Stellenmeldepflicht: Monitoringbericht 2023," *Staatssekretariat für Wirtschaft (SECO), Bern, Switzerland*.

Škoda, S. (2022): "Directing job search in practice: mandating pay information in job ads," Tech. rep., Working Paper, University of Zurich, Zurich.

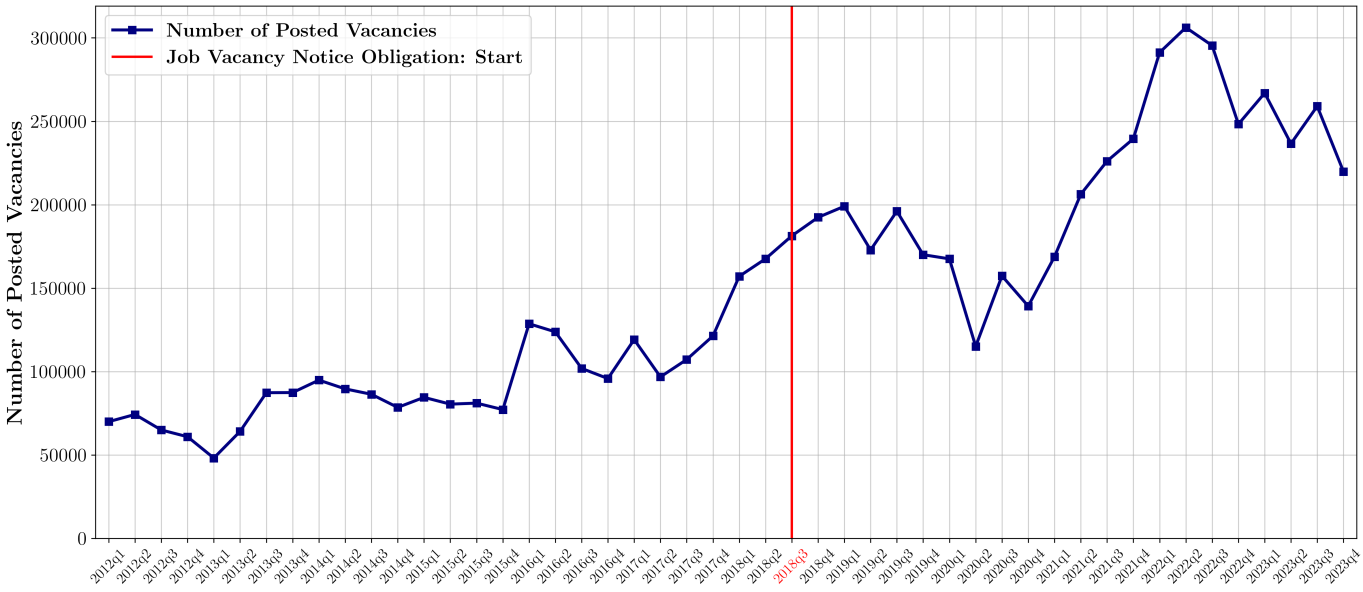
Stellenmarkt-Monitor Schweiz (2018): "Stellenausschreibungen auf den Webseiten von Schweizer Unternehmen. Abschätzen der Ausschöpfung durch die x28-Erhebungs-Technologie," *Universität Zürich*.

van der Klaauw, B. and H. Vethaak (2022): "Empirical evaluation of broader job search requirements for unemployed workers," *Working paper*.

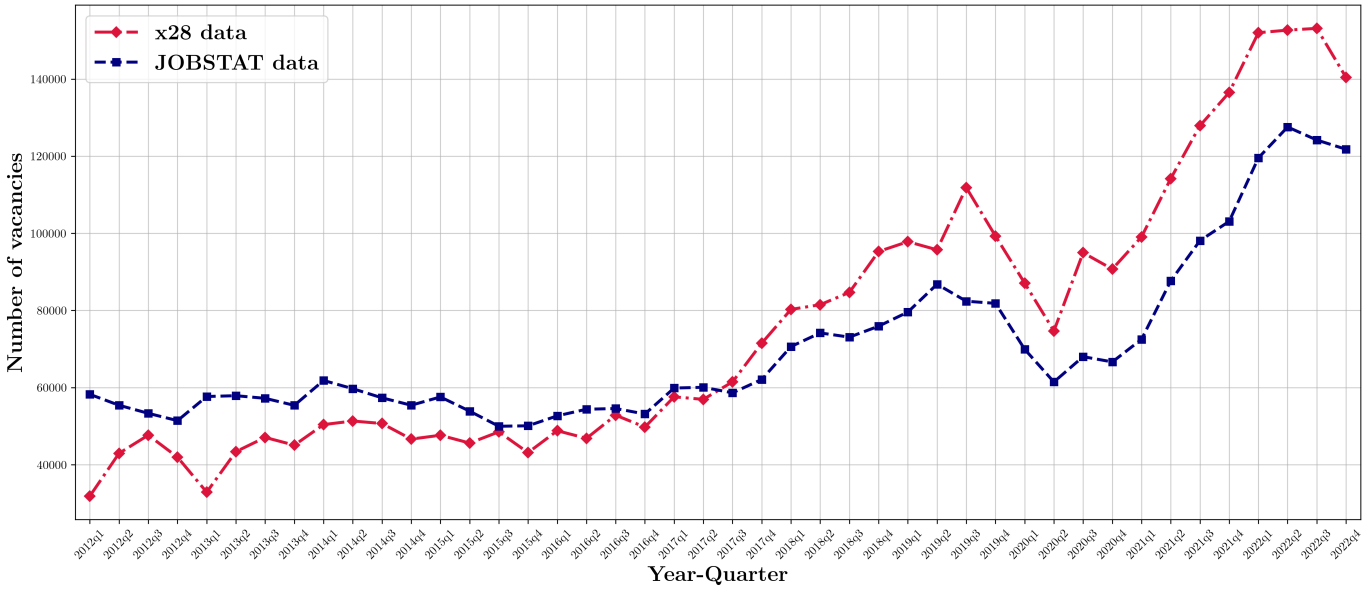
Additional Figures

Figure F1: Job Postings data

(a) Before and After JVNO



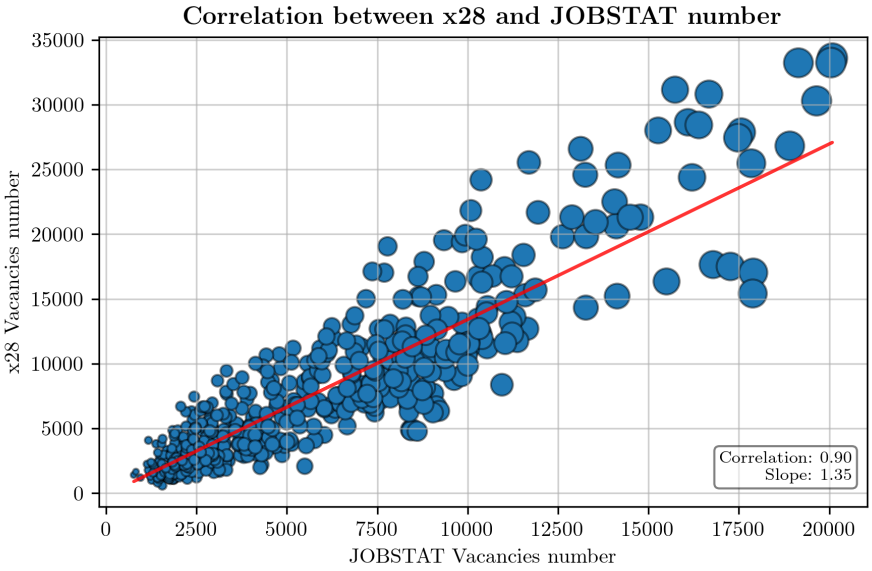
(b) Comparison with Administrative Vacancy Data



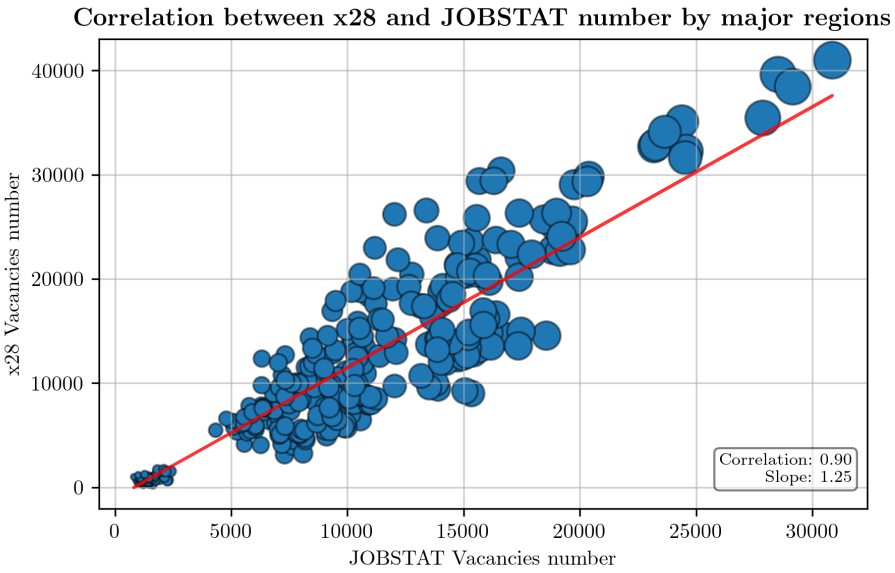
Panel (a) plots the number of Job Posting over the year quarters, the red line is the quarter when JVNO was introduced (2018q3). Panel (b) compares our Job Posting dataset (x28) with the number of vacancies from the administrative vacancy dataset (JOBSTAT). The number of Job Posting in our dataset shows the number of vacancies that were open and yet closed the last day of each quarter to be comparable with the data in the administrative vacancy data.

Figure F2: Comparison between our Job Postings data and JOBSTAT vacancy data

(a) Industries



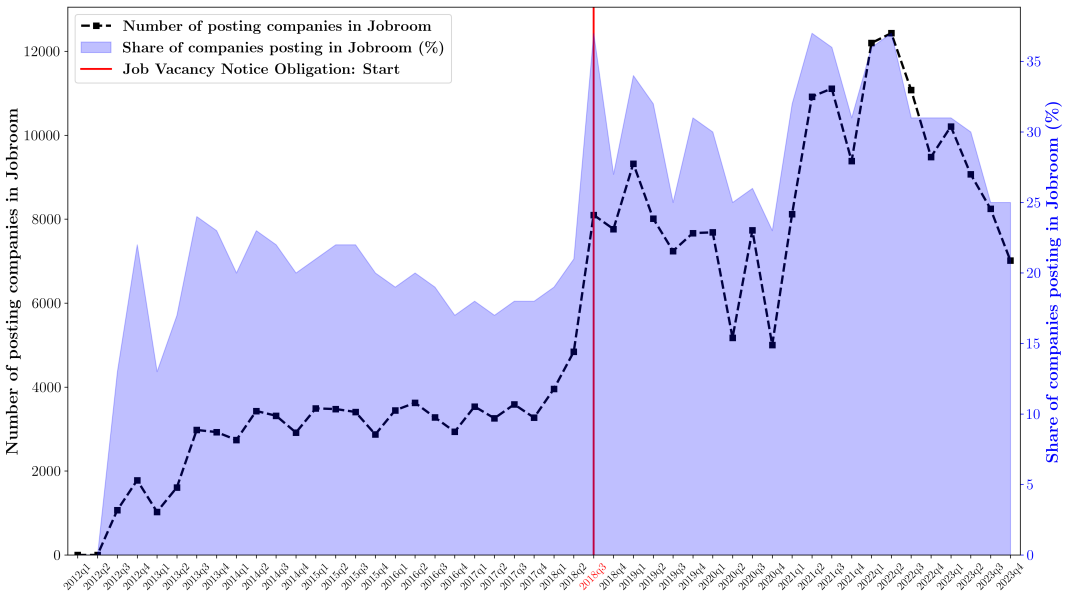
(b) Major regions



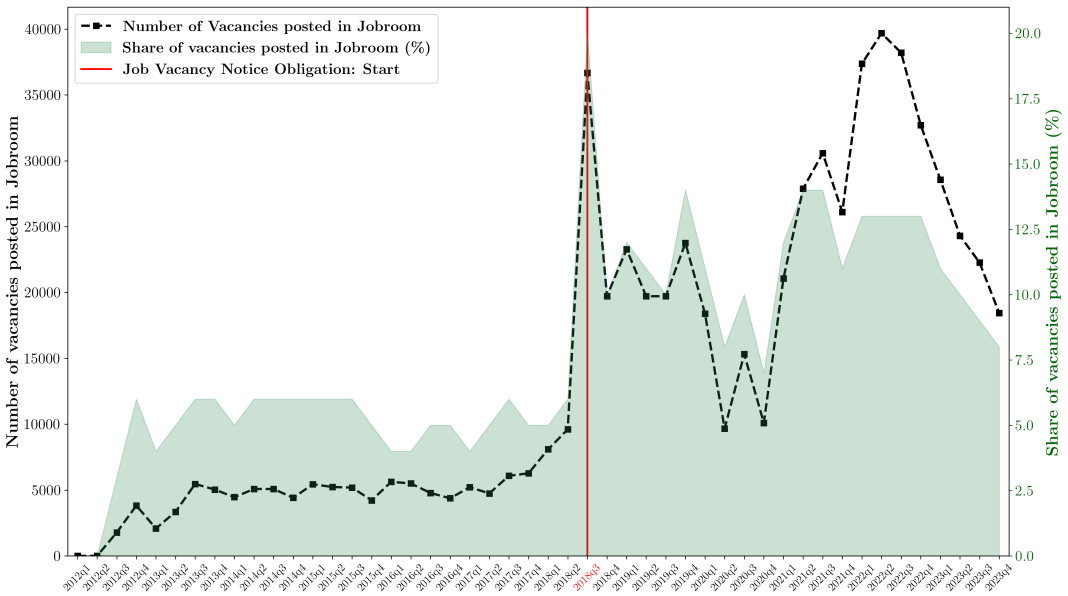
The figures compare the number of vacancies between our online Job Posting data (x28) and JOBSTAT. The number of vacancies represents those that were open and closed by the last day of each quarter to ensure comparability with the data in the JOBSTAT dataset. Each circle represents a combination of a year-quarter and an industry code (a) or a major geographical region (b). The circles' size, as well as the slopes and correlations, are computed with weighting based on the number of vacancies for that cell in the JOBSTAT dataset.

Figure F3: Effect of JVNO on the usage of Jobroom

(a) Number of firms posting in Jobroom



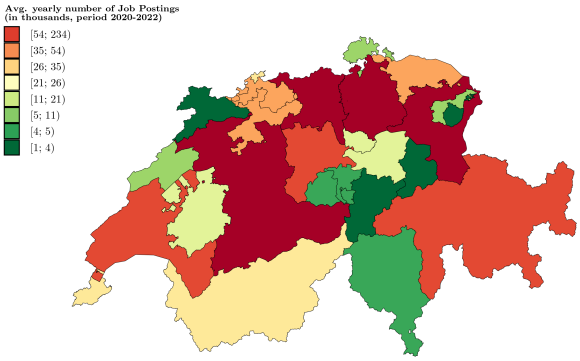
(b) Number of vacancies posted in Jobroom



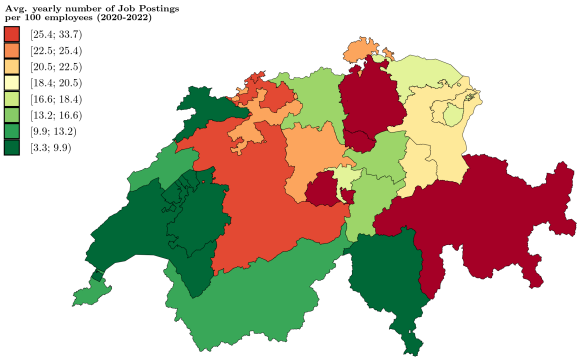
The figures show (a) the number of firms that have posted at least a vacancy on Jobroom for each quarter and (b) the number of vacancies posted in jobroom. The left axis and the line show the absolute number of firms or postings while the area and the right axis shows their share in respect to the total number of firms or vacancy. The red line at the third quarter of 2018 highligths the start of the JVNO policy.

Figure F4: Number of vacancies by cantons

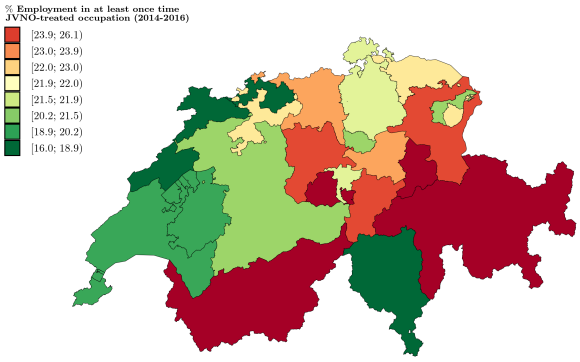
(a) Thousand of Job Postings



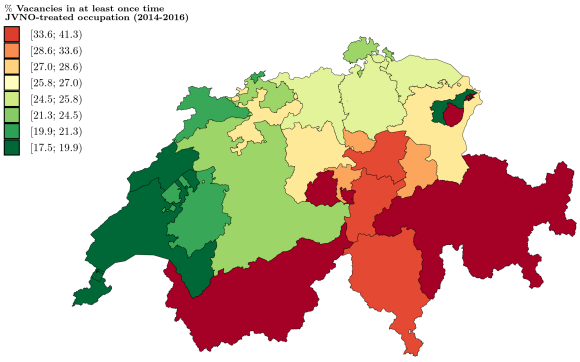
(b) Job Postings per 100 employees



(c) Employment in treated occupations

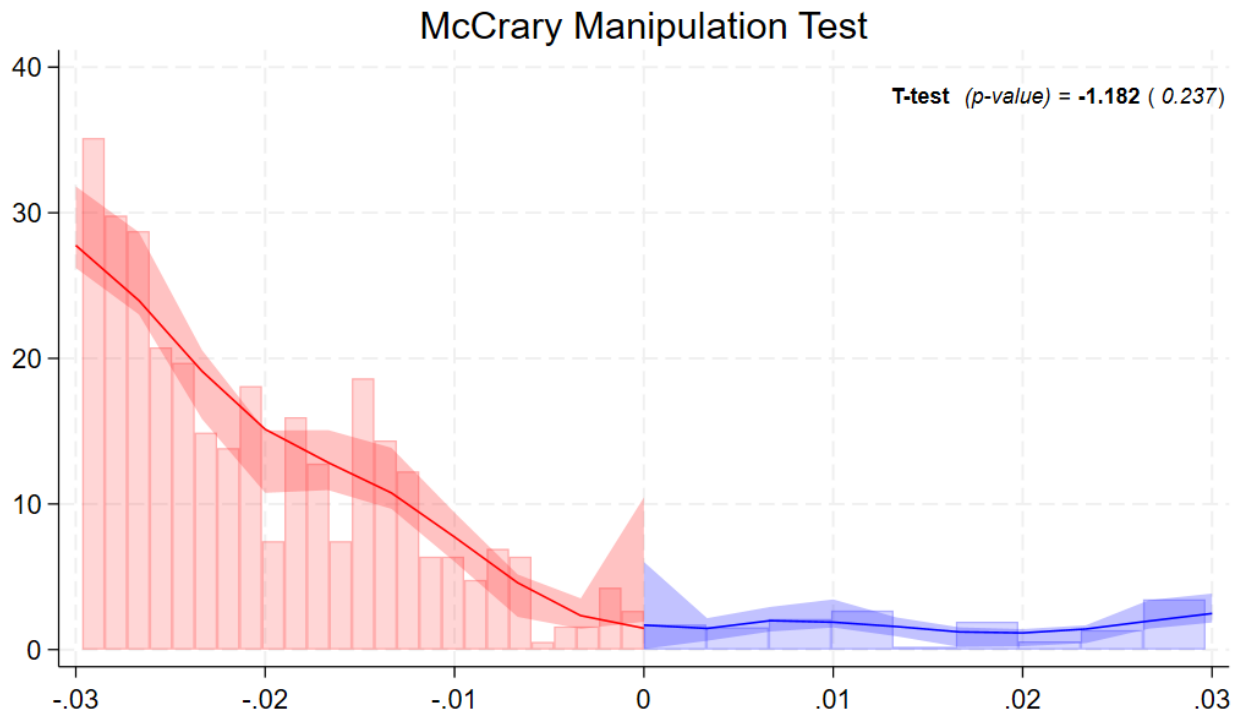


(d) Job Postings in treated occupations



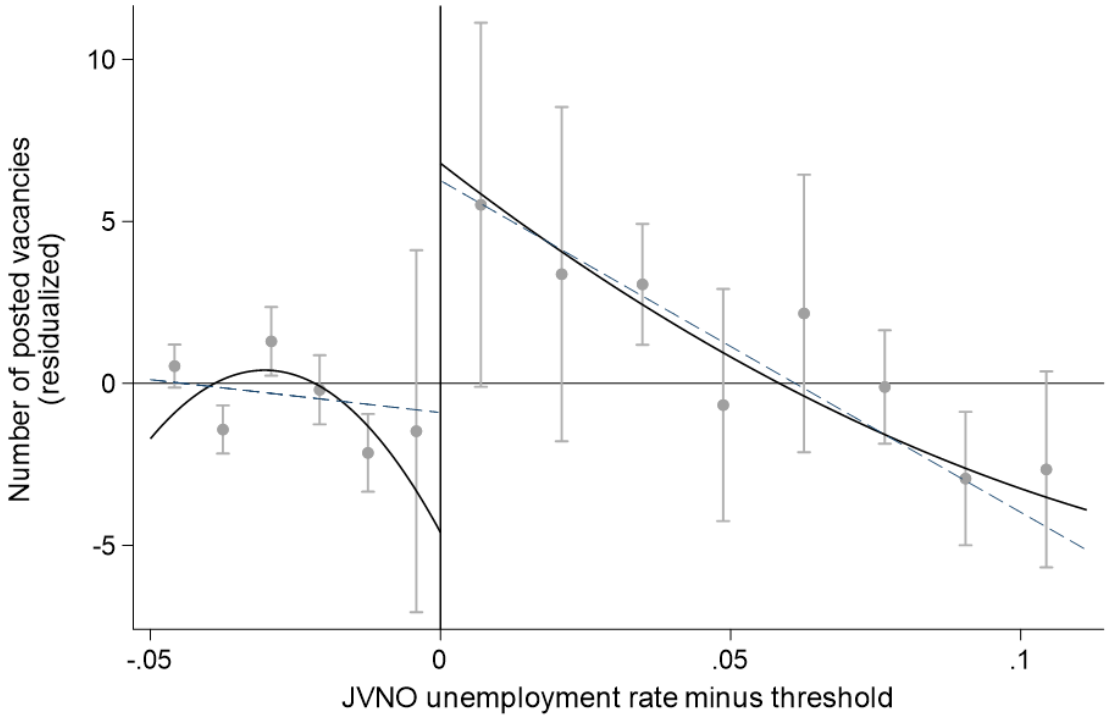
The figures divide Switzerland's 26 cantons into octiles. Panel (a) shows the average yearly thousand of job postings in each Swiss canton for the period 2020–2022. Panel (b) presents the average yearly number of job postings per 100 employees for the same period. Panel (c) depicts the percentage of employees working in occupations treated at least once by the JVNO policy. These percentages are calculated based on the pre-policy period (2014–2016). Panel (d) displays the share of job postings in occupations treated at least once by the JVNO policy, with percentages similarly computed using the pre-policy period (2014–2016).

Figure F5: Manipulation test for sorting into treatment



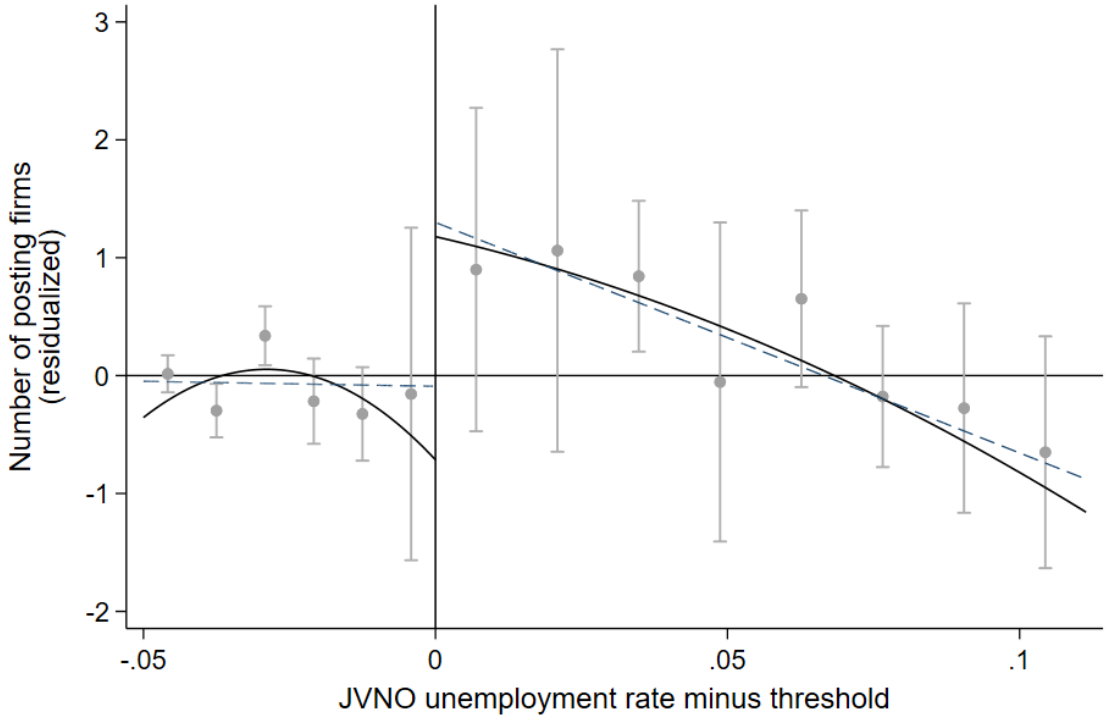
Notes: The Figure presents the sample distribution of the JVNO unemployment rate minus the threshold for occupations that were not treated by JVNO (in red) and those that were treated (in blue). The solid curves are the density estimates using local quadratic approximations and a triangular kernel along with bias-adjusted 95% confidence intervals (shaded areas). The density test fails to reject the null hypothesis of equal density at the cutoff with a robust p-value equal to 0.237.

Figure F6: Residualized changes in Job Postings close to the cutoff



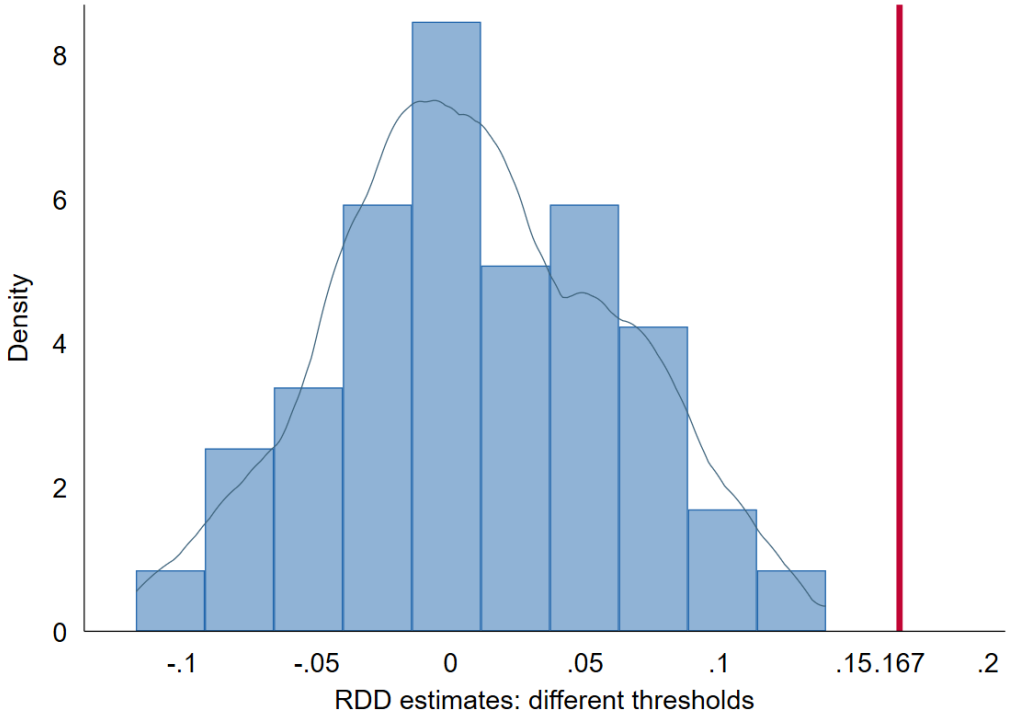
Notes: The Figure shows local means of the residualized number of job postings, net of canton, occupation, and year fixed effects, over the JVNO-relevant unemployment rate minus the threshold (i.e. the running variable). Local averages (dots) are calculated within equal-spaced bins of the running variable, which assigns cells to JVNO treatment if it is positive. Each cell consists in a combination between a canton, an occupation, and a year-quarter in the period 2020-2023. 95% confidence intervals (spikes) account for clustering at the canton level. The dashed lines denotes the linear fit and the solid curves the quadratic fits of the outcome on the running variable, which are allowed to differ on each side of the cutoff. Sample: Job Postings dataset, period 2020-2023.

Figure F7: Residualized changes in Posting Firms close to the cutoff



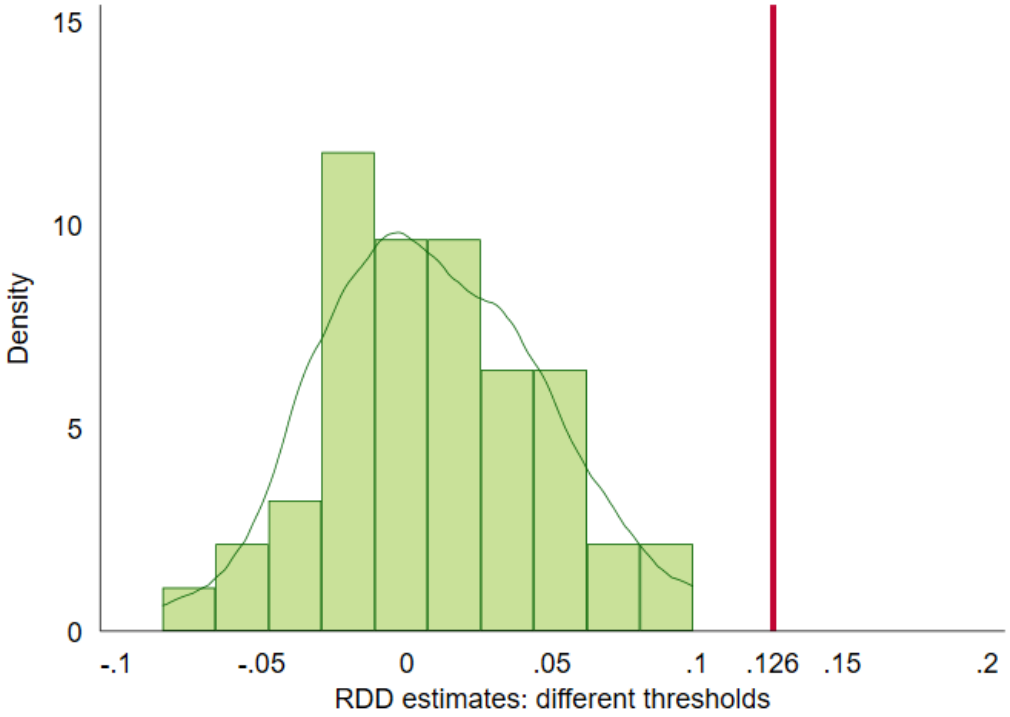
Notes: The Figure shows local means of the residualized number of posting firms, net of canton, occupation, and year fixed effects, over the JVNO-relevant unemployment rate minus the threshold (i.e. the running variable). Local averages (dots) are calculated within equal-spaced bins of the running variable, which assigns cells to JVNO treatment if it is positive. Each cell consists in a combination between a canton, an occupation, and a year-quarter in the period 2020-2023. 95% confidence intervals (spikes) account for clustering at the canton level. The dashed lines denotes the linear fit and the solid curves the quadratic fits of the outcome on the running variable, which are allowed to differ on each side of the cutoff. Sample: Job Postings dataset, period 2020-2023.

Figure F8: Permutation of the JVNO threshold: IHS. Job Postings



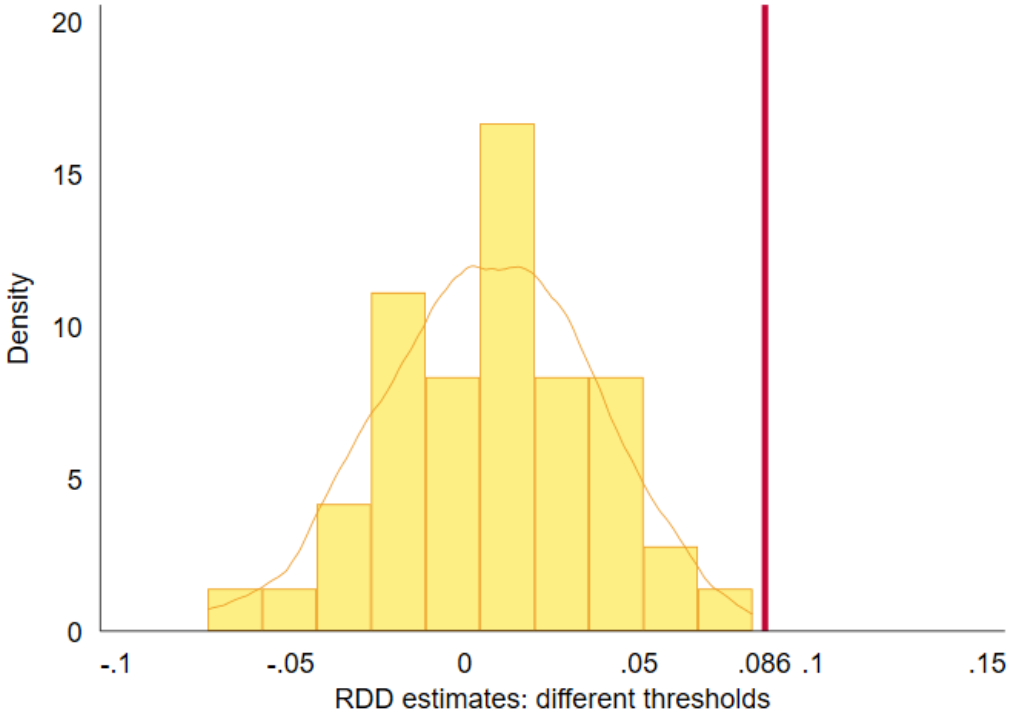
Notes: The figure illustrates the permutation test conducted to assess the sensitivity of the JVNO policy's effects on the number of job postings. Alternative, incorrect unemployment rate cutoffs for the JVNO policy were tested, specifically in 0.1 percentage point increments ranging from 1 to 4 percentage points and from 6.5 to 8 percentage points. RD estimates for these alternative cutoffs were obtained using the same specification as in Table 1, focusing on the IHS. number of job postings. The bars represent the histogram of these estimates, while the curve shows the kernel density of the distribution. The vertical red line indicates the estimate obtained with the actual threshold of 5 percentage points for the JVNO policy. All estimates include linear and quadratic fits, as well as canton, year-quarter, and occupation fixed effects. Sample: Job Postings dataset, period 2020-2023.

Figure F9: Permutation of the JVNO threshold: IHS. Posting Firms



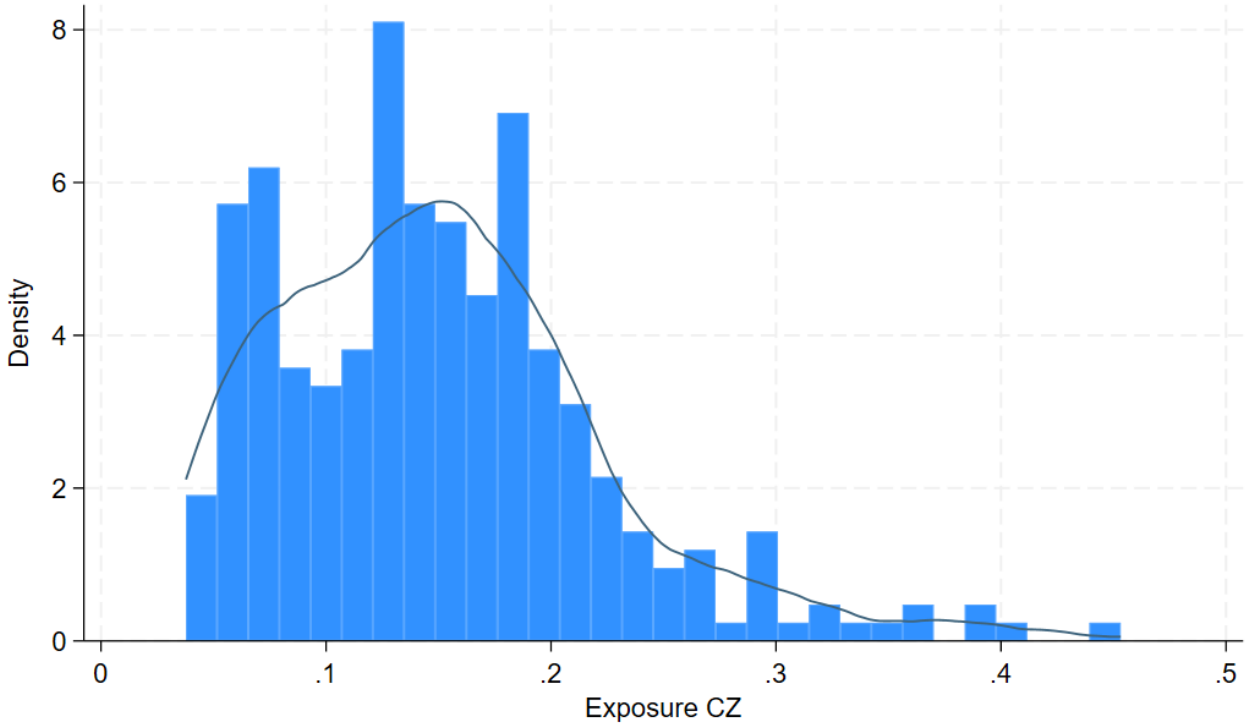
Notes: The figure illustrates the permutation test conducted to assess the sensitivity of the JVNO policy's effects on employment. Alternative, incorrect unemployment rate cutoffs for the JVNO policy were tested, specifically in 0.1 percentage point increments ranging from 1 to 4 percentage points and from 6.5 to 8 percentage points. RD estimates for these alternative cutoffs were obtained using the same specification as in Table 1, focusing on the IHS. number of posting firms. The bars represent the histogram of these estimates, while the curve shows the kernel density of the distribution. The vertical red line indicates the estimate obtained with the actual threshold of 5 percentage points for the JVNO policy. All estimates include linear and quadratic fits, as well as canton, year-quarter, and occupation fixed effects. Sample: Job Postings dataset, period 2020-2023.

Figure F10: Permutation of the JVNO threshold: Log. Employment



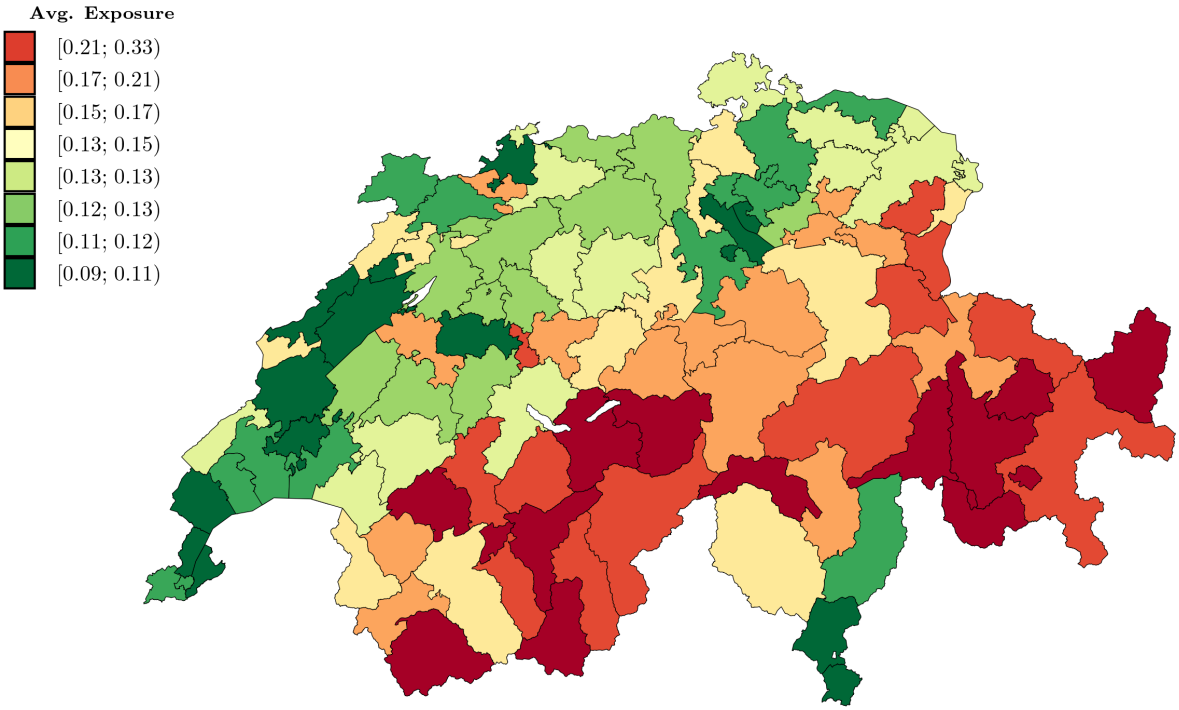
Notes: The figure illustrates the permutation test conducted to assess the sensitivity of the JVNO policy's effects on employment. Alternative, incorrect unemployment rate cutoffs for the JVNO policy were tested, specifically in 0.1 percentage point increments ranging from 1 to 4 percentage points and from 6.5 to 8 percentage points. RD estimates for these alternative cutoffs were obtained using the same specification as in Table 4, focusing on the log number of employed workers. The bars represent the histogram of these estimates, while the curve shows the kernel density of the distribution. The vertical red line indicates the estimate obtained with the actual threshold of 5 percentage points for the JVNO policy. All estimates include linear and quadratic fits, as well as canton, year, and occupation fixed effects. Sample: merged AVS and SE data, period 2020-2022.

Figure F11: Exposure per Commuting Zone: distribution



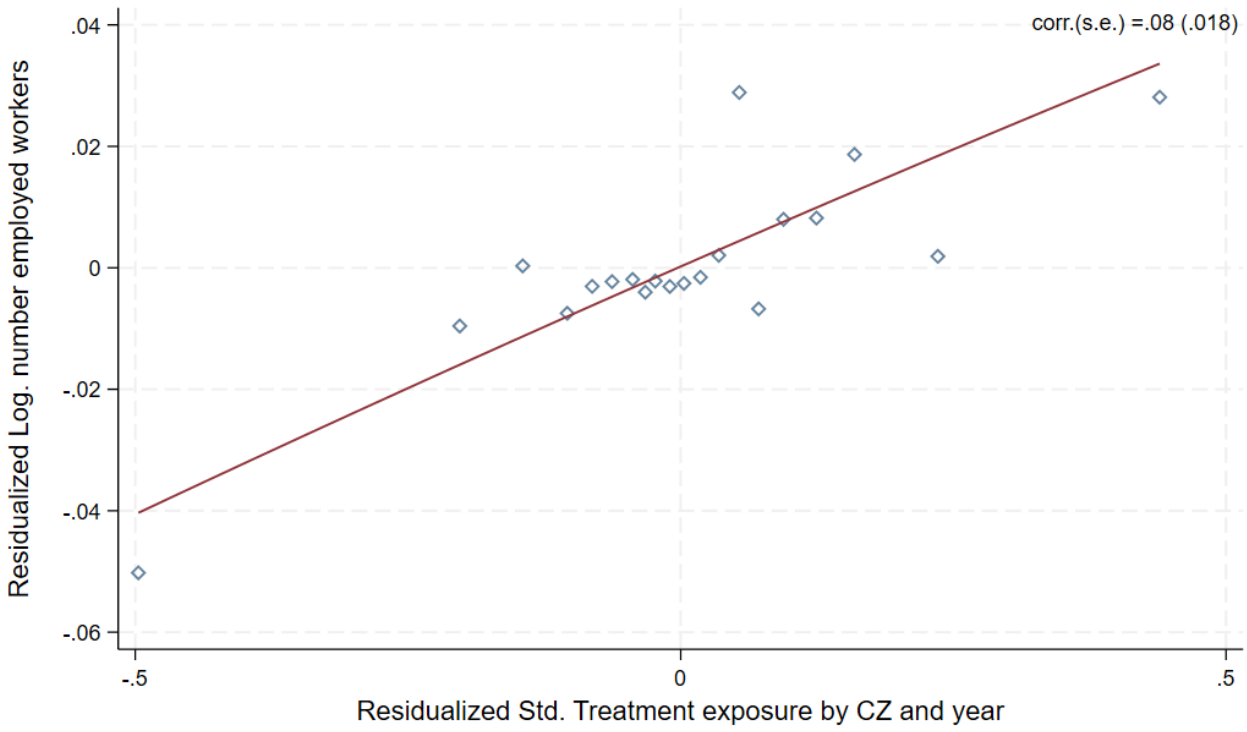
Notes: The figure shows the distribution of the Exposure measure, as in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. The pre-policy shares are constructed considering the years 2014-2016. Sample: Shares constructed using the merged AVS and SE datasets, period 2014-2016. Treatment, period 2020-2022.

Figure F12: Average Exposure per Commuting Zone: map



Notes: The figure shows the geographical dispersion of the Exposure measure, as in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. The pre-policy shares are constructed considering the years 2014-2016. The graph displays the average exposure per commuting zone over the treatment years 2020-2022. Sample: Shares constructed using the merged AVS and SE datasets, period 2014-2016. Treatment, period 2020-2022.

Figure F13: Residualized Binned scatter plot of std. Exposure on Log. Employment at the Commuting zone level



Notes: The figure displays the binned scatter plot between the residualized log. number of employees and the residualized standardized exposure measure. Both variables are constructed at the commuting zone times year level, and they are residualized with respect to commuting zone and year fixed effects. The standardized exposure measure, as in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. The pre-policy shares are constructed considering the years 2014-2016. Samples: Shares constructed using the merged AVS and SE datasets, period 2014-2016. Treatment, AVS data in the period 2020-2022.

Additional Tables

Table T1: Distribution of the JVNO-treated occupations (2020-2023)

	ISCO 4dg		Job Postings	
Group	Distinct	Share	Number	Share
Treated at least one time	50	13.93%	943,097	23.60%
Treated one time	5	1.39%	315,793	7.90%
Treated two times	13	3.62%	229,663	5.75%
Treated three times	10	2.79%	176,522	4.42%
Treated four times	22	6.13%	221,119	5.53%
Never treated	309	86.07%	3,053,025	76.40%

Notes: This table displays the share of 4-digit ISCO occupations treated by the JVNO policy across different rounds, along with their share of job postings. The row labeled "*Treated at least one time*" indicates the number of occupations (and the corresponding job postings) that were treated at least once under the JVNO policy during the period 2020–2023.

Table T2: Protected occupations by Major group (ISCO 1digit)

	Share Treated	
ISCO 1dg Description	ISCO 4dg	Employment
Managers	3.45	11.66
Professionals	7.69	7.84
Technicians and Associate Professionals	3.70	5.35
Clerical Support Workers	32.14	8.92
Service and Sales Workers	15.00	53.81
Skilled Agricultural, Forestry and Fishery Workers	0.00	0.00
Craft and Related Trades	15.87	16.06
Plant and Machine Operators, and Assemblers	16.22	34.17
Elementary Occupations	80.65	82.57

Notes: This table presents the share of 4-digit occupation codes within each 1-digit major occupation group that were treated by the JVNO policy at least once during the period 2020–2023. The column labeled "Employment" shows the share of workers employed in these treated 4-digit occupations within each 1-digit occupation group, calculated based on the pre-JVNO period (2014–2016).

Table T3: Effects on Job Postings and Posting firms: varying bandwidth

	Postings			Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.299***	0.181***	0.102***	0.116**	0.098***	0.069***
	(0.064)	(0.027)	(0.020)	(0.048)	(0.021)	(0.014)
$(u - u_0)$ & $Tr \times (u - u_0)$	✓	✓	✓	✓	✓	✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	2.44	2.21	2.1	2.09	1.85	1.75
N	9,464	30,576	69,888	9,464	30,576	69,888
R^2	0.891	0.862	0.856	0.897	0.875	0.870
Bandwidth	+/- 1%	+/- 2%	+/- 3%	+/- 1%	+/- 2%	+/- 3%

Notes: This table shows the Regression Discontinuity estimates for β in equation 1. The dependent variables are the inverse hyperbolic sine transformation of the number of job postings (1-3), inverse hyperbolic sine transformation of the number of posting firms (4-6). Bandwidth identifies the interval within which the analysis is carried out. The variables are measured at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatment" is a dummy variable taking value 1 if in that year-quarter that specific occupation was treated by the JVNO policy, i.e. it had an unemployment rate above the threshold (u_0). $(u - u_0)$ & $TR \times (u - u_0)$ denotes the linear fit of the RDD. All specifications includes Canton, Year-quarter, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: Job Postings dataset, period 2020-2023. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T4: PPML Effects on labor demand outcomes

	Postings - PPML		Firms - PPML		HHI - PPML	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.070***	0.160***	0.024***	0.067***	-0.035*	-0.038
	(0.016)	(0.019)	(0.008)	(0.008)	(0.020)	(0.026)
$(u - u_0)$ & $Tr \times (u - u_0)$	✓	✓	✓	✓	✓	✓
$(u - u_0)^2$ & $Tr \times (u - u_0)^2$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	32.9	2.2	1.82	1.82	4,250	4,250
N	140,192	140,192	140,192	140,192	97,509	97,509
pseudo-R^2	0.900	0.900	0.880	0.880	0.633	0.633

Notes: This table shows the Regression Discontinuity estimates for β in equation 1, using a Poisson Pseudo-Maximum Likelihood estimation. The dependent variables are the number of job postings (1-2), the number of posting firms (3-4), and the Herfindahl-Hirschman Index (5-6). The variables are measured at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatment" is a dummy variable taking value 1 if in that year-quarter that specific occupation was treated by the JVNO policy, i.e. it had an unemployment rate above the threshold (u_0). $(u - u_0)$ & $TR \times (u - u_0)$ $(u - u_0)^2$ & $TR \times (u - u_0)^2$ denote respectively the linear and quadratic fit of the RDD. All specifications includes Canton, Year-quarter, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: Job Postings dataset, period 2020-2023. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T5: Placebo Effects on labor demand outcomes

	Postings - IHS		Firms - IHS		HHI - Log	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.070	0.101*	0.023	0.029	-0.004	-0.027
	(0.052)	(0.054)	(0.039)	(0.040)	(0.041)	(0.044)
$(u - u_0)$ & $Tr \times (u - u_0)$	✓	✓	✓	✓	✓	✓
$(u - u_0)^2$ & $Tr \times (u - u_0)^2$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	1.49	1.49	1.24	1.24	8.04	8.04
N	86,736	86,736	86,736	86,736	46,451	46,451
R^2	0.807	0.807	0.823	0.823	0.757	0.757

Notes: This table shows the placebo check consisting in the Regression Discontinuity estimates for β in equation 1 for an incorrected imputed JVNO policy in the years 2016 and 2017. The dependent variables are the inverse hyperbolic sine transformation of the number of job postings (1-2), inverse hyperbolic sine transformation of the number of posting firms (3-4), and the logarithmic transformation of the Herfindahl-Hirschman Index (5-6). The variables are measured at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatment" is a dummy variable taking value 1 if in that year-quarter that specific occupation had an unemployment rate above the 5 percentage points threshold (u_0) imitating the JVNO policy. $(u-u_0)$ & $TR \times (u-u_0)$ $(u-u_0)^2$ & $TR \times (u-u_0)^2$ denote respectively the linear and quadratic fit of the RDD. All specifications includes Canton, Year-quarter, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: Job Postings dataset, period 2016-2017. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T6: Robustness: Different RD specifications

Dependent Variable:	*Postings - IHS*			*Firms - IHS*		
	RDRobust (1)	RDRobust (2)	RDHonest (3)	RDRobust (4)	RDRobust (5)	RDHonest (6)
Treatment	0.257**	0.163*	0.266***	0.178	0.391***	0.315***
	(0.038)	(0.087)	(0.079)	(0.034)	(0.056)	(0.068)
Specification	linear	quadratic		linear	quadratic	
Canton FE	✓	✓	✓	✓	✓	✓
Year × Quarter FE	✓	✓	✓	✓	✓	✓
Occupation (ISCO4) FE	✓	✓	✓	✓	✓	✓
Eff. number obs.	6,864	3,640	4,290	5,720	5,720	4,405
Rob. p-value	*0.012*	*0.096*	*0.000*	*0.526*	*0.000*	*0.000*

Notes: This table reports the RD estimates of the effect of JVNO on the IHS number of job postings (1-3) and IHS number of posting firms (4-6). All the dependent variables are computed at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatment" is a dummy variable taking value 1 if in that year-quarter that specific occupation was treated by the JVNO policy, i.e. it had an unemployment rate above the threshold (u_0). RDRobust shows the results in the Calonico et al. (2014) optimal bandwidth, with a triangular kernal and a linear polynomial (1,4) and a quadratic polynomial (2,5) of the unemployment rate. RDHonest shows the results implementing the Armstrong and Kolesár (2018) RD model. All specifications includes Canton, Year-quarter, and Occupation fixed effects. Conventional standard error in parantheses. Robust p-value report the robust-bias corrected p.value. Eff. number obs. reports the effective number of observations used in the estimations. Sample: Job Postings dataset: 2020-2023. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T7: Spillover or Employers manipulation across related occupations

	Postings - IHS		Firms - IHS		HHI - Log	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatm. related	0.009	0.018	-0.005	0.004	0.013	-0.001
	(0.014)	(0.014)	(0.010)	(0.010)	(0.012)	(0.012)
$(u - u_0)$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	1.88	1.88	1.55	1.55	7.88	7.88
N	164,736	164,736	164,736	164,736	97,509	97,509
R^2	0.842	0.842	0.858	0.858	0.742	0.742

Notes: This table reports the JVNO effects on occupations that were not treated but belong to the same 3-digit ISCO code as at least one treated 4-digit occupation. The dependent variables are the inverse hyperbolic sine transformation of the number of job postings (1-2), inverse hyperbolic sine transformation of the number of posting firms (3-4), and the logarithmic transformation of the Herfindahl-Hirschman Index (5-6). The variables are measured at the combination between an occupation (4-digit ISCO), a Canton, and a year-quarter. The independent variable "Treatm. related" is a dummy variable taking value 1 if the 4digit occupation is not directly treat by JVNO, but it belongs to the same 3-digit ISCO code as at least one treated 4-digit occupation. $(u - u_0)$ denotes the additional control for the JVNO unemployment rate. All specifications includes Canton, Year-quarter, and Occupation fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses, clustered at the Canton level. Sample: Job Postings dataset, period 2020-2023. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T8: Exposure effect on Earnings by Nationality

		Nationality		Non Swiss, arrival date		
	Total	Swiss	Non Swiss	<1 year	2-10 years	>10 years
Exposure	0.006*	0.015***	0.005	0.009	0.042***	0.016**
	(0.003)	(0.003)	(0.005)	(0.020)	(0.009)	(0.007)
CZ	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
MDV	8.66	8.68	8.59	8.5	8.61	8.6
N	303	303	303	303	303	303
R^2	0.998	0.997	0.997	0.969	0.992	0.989

Notes: This table shows the effect of JVNO exposure measure on the Log. average monthly earnings, disaggregated by nationality. All the dependent variables are computed at the combination between a commuting zone and a year, considering all the individuals between 20 and 65 years old. In the columns Swiss and Non Swiss the dependent variable is computed considering only Swiss and Non Swiss individuals, respectively. Finally, the last three columns computed the log. average monthly earnings per non Swiss individuals that arrived in Switzerland that year ($< 1year$), between 2 and 10 years ago ($2 - 10years$) and more than 10 years ago ($> 10years$). The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T9: Exposure effect on Employment by Nationality and closeness to the Swiss border

		Nationality		Non Swiss, arrival date		
	Total	Swiss	Non Swiss	<1 year	2-10 years	>10 years
Exposure	0.087***	0.045**	0.151***	0.190***	0.106***	0.055**
	(0.021)	(0.019)	(0.028)	(0.052)	(0.027)	(0.022)
Border CZ × Exposure	0.051***	0.046***	0.050***	0.047	0.050***	0.042***
	(0.012)	(0.010)	(0.016)	(0.029)	(0.015)	(0.012)
CZ	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
MDV	10.1	9.82	8.79	6.19	7.88	8.07
N	303	303	303	303	303	303
R^2	0.997	0.998	0.996	0.984	0.996	0.998

Notes: This table shows the effect of JVNO exposure measure on the Log. number of employed workers, disaggregated by nationality. All the dependent variables are computed at the combination between a commuting zone and a year, considering all the individuals between 20 and 65 years old. In the columns Swiss and Non Swiss the dependent variable is computed considering only Swiss and Non Swiss individuals, respectively. Finally, the last three columns computed the Log. number of employed workers per non Swiss individuals that arrived in Switzerland that year ($< 1year$), between 2 and 10 years ago ($2 - 10years$) and more than 10 years ago ($> 10years$). The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. The independent variable "Bordering CZ" is a dummy variable that takes value equal to 1 if the commuting zone has an average distance from the border that is less than 20 kms. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T10: Exposure effect on Population by Nationality

		Nationality		Non Swiss, arrival date		
	Total	Swiss	Non Swiss	<1 year	2-10 years	>10 years
Exposure	0.077***	0.041**	0.138***	0.077	0.112***	0.058**
	(0.022)	(0.020)	(0.030)	(0.054)	(0.030)	(0.024)
CZ	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
MDV	10.4	10.1	9.08	6.77	8.16	8.33
N	303	303	303	303	303	303
R^2	0.997	0.997	0.996	0.983	0.996	0.997

Notes: This table shows the effect of JVNO exposure measure on the Log. number of individuals by nationality. All the dependent variables are computed at the combination between a commuting zone and a year, considering all the individuals between 20 and 65 years old. In the columns Swiss and Non Swiss the dependent variable is computed considering only Swiss and Non Swiss individuals, respectively. Finally, the last three columns computed the log number of non Swiss individuals that arrived in Switzerland that year ($< 1year$), between 2 and 10 years ago ($2 - 10years$) and more than 10 years ago ($> 10years$). The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T11: Exposure effect on Population share by Nationality

	Nationality		Non Swiss, arrival date		
	Swiss	Non Swiss	<1 year	2-10 years	>10 years
Exposure	-2.172***	2.172***	2.199***	0.352**	-0.380***
	(0.274)	(0.274)	(0.177)	(0.138)	(0.068)
CZ	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
MDV	71.5	28.5	3.54	11.5	13.5
N	303	303	303	303	303
R^2	0.994	0.994	0.982	0.993	0.998

Notes: This table shows the effect of JVNO exposure measure on the share of individuals by nationality over the total population. All the dependent variables are computed at the combination between a commuting zone and a year, considering all the individuals between 20 and 65 years old. In the columns Swiss and Non Swiss the dependent variable is computed considering only Swiss and Non Swiss individuals, respectively. Finally, the last three columns computed the share of non Swiss individuals that arrived in Switzerland that year ($< 1year$), between 2 and 10 years ago ($2 - 10years$) and more than 10 years ago ($> 10years$) over the all population for that year in that commuting zone. The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.

Table T12: Placebo check on the Exposure effect on Employment by Nationality

		Nationality		Non Swiss, arrival date		
	Total	Swiss	Non Swiss	<1 year	2-10 years	>10 years
Placebo Exposure	-0.002	-0.009	0.005	0.049	-0.032***	0.022**
	(0.006)	(0.006)	(0.008)	(0.033)	(0.010)	(0.009)
CZ	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
MDV	10.1	9.79	8.7	6.08	7.83	7.95
N	303	303	303	303	303	303
R^2	1.000	1.000	1.000	0.994	1.000	1.000

This table presents a placebo check, performed by retro-dating the JVNO exposure measure by three years, to a period before the implementation of the JVNO policy. It investigates its effect on the log number of employed workers, disaggregated by nationality. All dependent variables are calculated at the commuting zone-year level, considering individuals aged 20 to 65. In the columns Swiss and Non Swiss the dependent variable is computed considering only Swiss and Non Swiss individuals, respectively. Finally, the last three columns computed the log number of employed non Swiss individuals that arrived in Switzerland that year ($< 1year$), between 2 and 10 years ago ($2 - 10years$) and more than 10 years ago ($> 10years$). The independent variable "Exposure" is the standardized exposure measure, defined in Equation 2, constructed as the sum of the pre-policy shares of workers employed in a treated occupation in that year. All specifications includes commuting zone (CZ) and Year fixed effects. MDV shows the mean of the dependent variable. Robust standard errors in parentheses. Samples: Pre-policy shares constructed using the SE data from 2014 to 2016. Outcome variables are constructed using the AVS data, period 2020-2022. *p < 0.10, **p < 0.05, ***p < 0.01.