Effects of Mandatory Job Postings on Labor Market Outcomes

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Abstract

This paper studies how mandating job postings impacts firms' recruiting practices, employment, and wages, exploiting the Swiss Job Vacancy Notice Obligation (JVNO) policy, which requires firms hiring in high-unemployment occupations to post vacancies on a public online platform. We leverage administrative data and estimate two empirical models: a regression discontinuity design comparing occupations around the unemployment rate threshold and a firm-level shift-share approach capturing differential exposure to treated occupations. We find that the policy leads to a significant increase in both job postings and posting firms in treated occupations, with effects driven primarily by smaller firms. Firm-level evidence shows that these changes reflect a genuine expansion in employment rather than a simple reallocation of hiring activity, and are accompanied by increases in wages. We further document higher exit rates from unemployment to treated occupations with no corresponding increase in job search activity. Taken together, the results indicate that mandatory job postings can improve matching efficiency by increasing vacancy creation and improving the allocation of workers to jobs.

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 is central to labor market performance, yet persistent frictions remain. Job seekers face difficulties identifying relevant opportunities and navigating applications, while firms struggle to attract suitable candidates and fill vacancies quickly. Policy responses have largely targeted the supply side. Training programs, job search assistance, and incentives for active search aim to improve job seekers' behavior, with mixed success depending on how well they align with local labor market conditions.[1] However, comparatively little attention has been paid to inefficiencies from informal hiring on the demand side.[2] Firms frequently rely on informal hiring channels, e.g. employee referrals, personal networks, and intermediaries, that restrict access for less-connected workers and limit the visibility of vacancies.[3] By contrast, formal hiring through publicly posted vacancies expands the set of potential applicants and may improve match quality. Whether shifting firms from informal to formal hiring improves matching efficiency remains an open empirical question.

This paper fills this gap by studying the effects of mandating vacancy posting on labor market outcomes. We exploit the Swiss Job Vacancy Notification Obligation (JVNO), a federal policy that requires firms hiring in high-unemployment occupations to post vacancies on a centralized platform and prohibits external advertising for five days. During this period, vacancies are visible only to registered job seekers, effectively restricting firms' ability to rely on informal hiring channels. Coverage is determined by occupation-specific unemployment thresholds, generating annual variation in the set of covered occupations.

Policies that regulate hiring can impose frictions on firms while simultaneously expanding access to job opportunities. To understand how mandating vacancy posting impact the labor market we build search-and-matching model with decreasing returns to scale, wage rigidity, and firm heterogeneity. We allow firms to choose between informal and formal hiring, with formal hiring characterized by higher fixed costs and lower marginal costs. A key implication of the model is that a vacancy posting obligation can increase employment if a substantial number of firms switch

[1] For evaluations of Active Labor Market Policies (ALMPs), see Lalive et al. (2008), Caliendo and Schmidl (2016), Kluve et al. (2019), and Card et al. (2018). More recently, low-cost digital and AI-based tools have expanded job seekers' search sets and improved employment outcomes, particularly for less-educated workers (Belot et al., 2019; Le Barbanchon et al., 2023).

[2] Prior work has examined interventions that assist firms in recruitment or improve their understanding of labor market regulations (Algan et al., 2020; Bertrand and Crépon, 2021). Other employer-side policies include hiring credits (Bartik, 2001; Neumark and Grijalva, 2017; Cahuc et al., 2019), payroll incentives (Ku et al., 2020), and hiring quotas (McCrary, 2007), typically aimed at stimulating local employment or improving outcomes for disadvantaged groups.

[3] See Montgomery (1991); Pistaferri (1999); Bayer et al. (2008); Hensvik and Skans (2016). Informal hiring may also bypass wage transparency and anti-discrimination regulations (Bamieh and Ziegler, 2024; Frimmel et al., 2024; Škoda, 2022; Kuhn and Shen, 2013, 2023; Card et al., 2024).

from informal to formal hiring rather than exiting the market.

We then move to the empirical analysis, which leverages rich administrative employer–employee data with comprehensive web-scraped data on online job postings. The job postings dataset covers the universe of online vacancies in Switzerland from 2012 to 2024 and captures approximately 95% of all posted job ads, providing a detailed measure of formal recruitment activity. We complement this with a census of all firms with at least one employee, which contains information on the number of workers, but has no information on occupation. The firm census allows us to study the effects of the policy on firm-level employment. We further construct a matched employer–employee dataset using social security records, which provides information on workers' characteristics and earnings, but does not have occupation. Finally, we use administrative data from the unemployment register to analyze job seekers' transitions into employment.

Using a regression discontinuity design (RDD) that compares occupations just above and below the JVNO eligibility threshold, we estimate the effect of the policy on formal labor demand. The JVNO leads to a substantial increase in vacancy posting at the threshold: the number of job postings rises by approximately 17 percent, and the number of posting firms increases by nearly 13 percent. We also observe a decline in vacancy concentration, indicating that hiring activity becomes less concentrated across firms. These effects are primarily driven by small firms and by firms that had not previously posted vacancies online, consistent with the policy expanding participation in formal hiring channels. In contrast, effects are markedly smaller for large firms already active online, suggesting diminishing returns or congestion from increased competition among posting firms.

A key concern is that the increase in postings may be a reporting effect, i.e. a shift from informal to formal recruitment rather than an expansion in total labor demand. To address this, we examine firm-level employment outcomes using the firm census and the matched sample. Because these data do not include occupational information, we proxy firms' exposure to the policy using industry-level variation. Specifically, we construct an industry-level exposure measure defined as the share of occupations covered by the JVNO, weighted by pre-policy employment shares within each industry.[4]

We find that firms more exposed to the policy experience a significant increase in employment in the firm census: the number of workers employed by firms rises by approximately 3.5 percent when moving from zero to full exposure. This pattern indicates that the increase in postings reflects genuine job creation rather than simple reclassification. The effects are again concentrated among

[4]This measure has a shift-share interpretation (Borusyak et al., 2025), where the shocks correspond to JVNO treatment assignment and the shares capture pre-policy occupational composition.

small firms. For large firms, the estimated employment effect is close to zero and imprecisely estimated.

Using the matched employer–employee data, we estimate that firms more exposed to the policy increase employment by about 1.6 percent. This effect is smaller than in the firm census, reflecting the under-representation of small firms in the matched dataset, where effects are strongest. The employment gains are concentrated among non-Swiss workers, both recent arrivals and those who entered Switzerland in earlier years. We also document a significant increase in wages of approximately 2.9 percent. Wage effects are positive and statistically significant for both Swiss and non-Swiss workers, with particularly strong effects for earlier immigrant cohorts. The joint increase in employment and wages suggests that the policy raises labor demand rather than inducing substitution toward lower-cost workers.

A key margin underlying the employment increase is hiring. Mandated vacancy posting raises the number of new hires by 6.6 percent, with similar effects for Swiss and non-Swiss workers. Wage effects for Swiss new hires are positive but not statistically significant, while for non-Swiss workers they are close to zero. New hires are significantly more likely to remain with the firm for at least two years, indicating that the additional matches are durable and of high quality despite higher hiring costs.

Job seekers are a primary target of the policy. Using the same regression discontinuity design applied to vacancy postings, we find that exits from unemployment into treated occupations increase by 4.6%, while entries into unemployment from the same occupations decline by 3.2%. Consistent with these flow dynamics, the job-finding rate in these occupations rises by 9.2%. Taken together, these results indicate an increase in market tightness, which facilitates faster job matching and reduces unemployment duration in affected occupations.

This paper contributes to several strands of the literature. First, it contributes to the literature on policies that reduce matching frictions in the labor market. Most existing work focuses on the supply side, studying job search assistance programs. A large body of evidence finds that such interventions can improve employment outcomes, particularly in weak labor demand environments (Card et al., 2018; Belot et al., 2019; Altmann et al., 2022; van der Klaauw and Vethaak, 2022), although their effectiveness depends on context and program design (Dhia et al., 2022). A smaller but growing literature studies demand-side policies that directly affect firms' hiring behavior, including hiring subsidies, tax incentives, and recruitment assistance (Neumark and Grijalva, 2017; Cahuc et al., 2019; Ku et al., 2020; McCrary, 2007; Bertrand and Crépon, 2021). Closest to our setting, Algan et al. (2020) study a reform of public employment services that improved vacancy filling by increasing the intensity and quality of intermediation between firms and job seekers.

They show that reducing information frictions and facilitating matching can significantly raise hiring outcomes, even without directly subsidizing firms. Our paper contributes to this literature by studying a policy that stimulates labor demand without relying on subsidies or large fiscal transfers. Instead, the JVNO mandates vacancy posting and facilitates intermediation, thereby increasing the visibility of job opportunities and improving matching. Relative to Algan et al. (2020), we emphasize a complementary mechanism: beyond improving matching efficiency, such policies can also activate new vacancy creation.

Second, we contribute to the literature on formal and informal hiring. A large body of work emphasizes the role of networks in shaping hiring outcomes, showing that informal channels can improve match quality but may also affect wages and sorting (Montgomery, 1991; Hensvik and Skans, 2016; Pistaferri, 1999; Bayer et al., 2008). More recent studies examine how online job posting and digital platforms improve matching efficiency (Bhuller et al., 2023; Fernando et al., 2023). Whereas this literature typically compares hiring channels or studies the adoption of recruitment technologies, we provide, to the best of our knowledge, the first large-scale evaluation of a policy that directly mandates formal vacancy posting. Our results highlight how shifting firms from informal to formal hiring can increase labor demand and improve matching outcomes.

Third, this paper relates to the literature on policies regulating hiring markets and job advertisement practices. Existing work has studied the effects of wage transparency and restrictions on job advertisements, showing impacts on wages, sorting, and hiring patterns (Frimmel et al., 2024; Bamieh and Ziegler, 2024; Škoda, 2022; Kuhn and Shen, 2013, 2023; Card et al., 2024). We complement this literature by focusing on a more fundamental margin: the visibility of vacancies themselves. By requiring firms to publicly post vacancies, the JVNO affects whether jobs become observable to workers in the first place. Our findings show that this form of transparency can substantially increase vacancy creation, improve job-finding rates, and enhance overall matching efficiency.

The remainder of the paper is structured as follows. Section 2 provides institutional background on the JVNO. Section 3 presents the conceptual framework and makes testable predictions. Section 4 describes the data and presents descriptive statistics. Section 5 presents the empirical models and the associated results. Section 6 concludes.

2 Institutional Background

Following the 2014 referendum on the initiative "Against Mass Immigration", the Swiss Parliament introduced the Job Vacancy Notification Obligation (JVNO) to improve the use of the

domestic labor market. Under the JVNO, employers must register vacancies in occupations whose unemployment rate meets or exceeds a specified threshold with a regional employment agency (REA). These 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.[5]

Within the first three working days after registration, REAs can inform employers whether suitable unemployed candidates are available. While employers are not required to interview these candidates, they must report the outcome of the referral process to the REA. Unemployed workers also have direct access to Jobroom.ch, allowing them to identify and apply for suitable vacancies 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 seven rounds through 2024, the most recent year covered by 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 October 1 to September 30. By November, SECO announces the occupations with unemployment rates exceeding 5%, which are then subject to JVNO requirements during the following calendar year, from January 1 to December 31.

The first JVNO implementation was an exception to this schedule. This initial round differed in several important respects. First, the unemployment rate threshold for treatment was set at 8 percent, rather than the 5 percent threshold applied in subsequent rounds. More importantly, the occupational classification system used during this period does not align with the ISCO 4-digit codes employed in our primary data sources. Because of these differences in timing, eligibility thresholds, and, most importantly, occupational classifications, we exclude the first JVNO round (2018–2019) from our main empirical analysis.[6]

Responsibility for monitoring and enforcing compliance with the JVNO policy lies with cantonal

[5]The only exemptions from the JVNO consist of cases in which the vacancy is filled by someone employed by 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.

[6]In the first round, the list of treated occupations was also reported using the new occupational classification (CH-ISCO 19); however, the unemployment rates were only provided under the older classification (SBN 2000). This inconsistency creates challenges for implementing the RD design, which requires a precise measure of the running variable. For this reason, we exclude the first round from the RD analysis. However, if we include this round and limit the analysis to occupations with a correctly predicted treatment status, the results remain robust. For the event-study and shift-share analyses, which are less sensitive to the precise measurement of the running variable, we include the first round to increase predictive power. Importantly, the main results from these approaches are not substantially affected by the inclusion or exclusion of the 2018–2019 period.

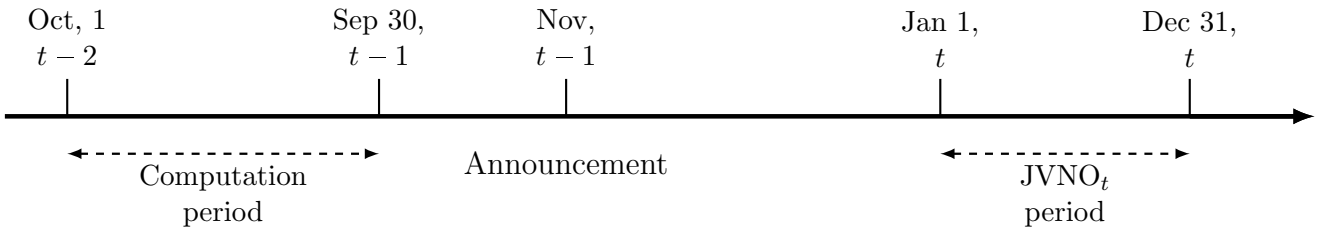


FIGURE 1: TIME-SCHEDULE FOR JVNO POLICY AT TIME t

authorities. Violations of the policy are subject to fines of up to CHF 40,000, or CHF 20,000 in cases of negligence. Compliance among employers has been high, with violations recorded in only about 1% of inspected cases.[7]

3 Conceptual Framework

To understand how a policy mandating firms to post vacancies online affects labor market outcomes, it is useful to distinguish between informal and formal hiring practices. Informal hiring typically relies on referrals, personal networks, or direct contacts, while formal hiring involves publicly advertising vacancies and selecting candidates through more structured procedures. These two hiring technologies differ in their cost structure, which plays a central role in our framework.

We develop a conceptual framework in which heterogeneous firms choose between informal and formal hiring to show how the JVNO shifts firms toward formal posting, affects vacancy creation and employment, and may also generate congestion and hiring exit among low-productivity firms. The full model is presented in Online Appendix A. Here, we focus on the main intuition.

We build on a random search and matching model with decreasing returns to scale, sticky wages, and firm heterogeneity, following Michaillat (2012) and Algan et al. (2020). We extend this framework by allowing firms to choose between formal and informal hiring technologies.

Formal versus informal hiring. Informal hiring is flexible and does not require any upfront investment, but it is relatively inefficient and difficult to scale, leading to higher marginal hiring costs. In contrast, formal hiring entails a fixed, non-recoverable setup cost F, but allows firms to recruit at lower marginal cost. This fixed cost can reflect the need to establish HR processes, adopt digital recruiting platforms, acquire organizational knowledge, or simply the cost of changing

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

established hiring habits. Once these systems are in place, however, formal hiring becomes easier to scale and allows firms to reach a broader pool of candidates, which we model it as a lower marginal cost.[8]

Firms differ in productivity a and produce output using labor according to

$$F(n) = an^{\alpha}, \quad \alpha \in (0,1). \tag{1}$$

Given market tightness θ, a firm choosing hiring technology $j \in \{F, I\}$ solves

$$\pi(n(a), \theta, j) = -F_j + \sum_{t=0}^{\infty} \beta^t (1-\delta)^t \left[an(a)^{\alpha} - wn(a) - \frac{k_j \lambda n(a)}{q(\theta)} \right], \tag{2}$$

where $k_F < k_I$ and $F_F > F_I = 0$.

This structure generates sorting across firms according to their productivity. As illustrated in Panel (a) of Figure 2, there exist two productivity thresholds, $\tilde{a}$ and $\hat{a}$, with $\tilde{a} < \hat{a}$. Firms with productivity below $\tilde{a}$ prefer informal hiring to both formal hiring and not hiring. Firms with productivity between $\tilde{a}$ and $\hat{a}$ also choose informal hiring, as it dominates formal hiring, while formal hiring is preferred to not hiring. Finally, firms with productivity above $\hat{a}$ adopt formal hiring, as it dominates informal hiring. This sorting reflects the trade-off between the fixed cost of formal hiring and its lower marginal cost.[9]

Labor demand and equilibrium. The labor market features search frictions. Let $\theta = v/u$ denote market tightness, and $q(\theta)$ the vacancy-filling rate. Following Michaillat (2012), firm-level labor demand satisfies:

$$F'(n) = w + \frac{k_j \left[1 - \beta(1-\lambda)(1-\delta)\right]}{\beta(1-\delta)q(\theta)}. \tag{3}$$

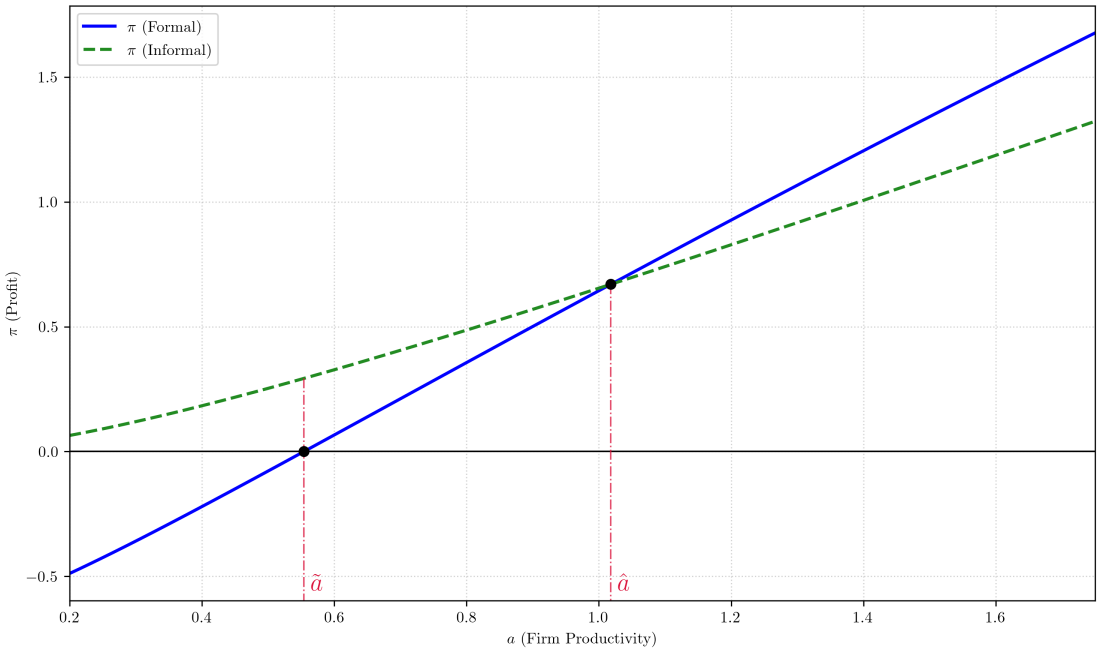
For a given θ, this condition defines labor demand $D(j, \theta)$ for each hiring technology.

Let τ denote the share of firms hiring formally. Aggregate labor demand is:

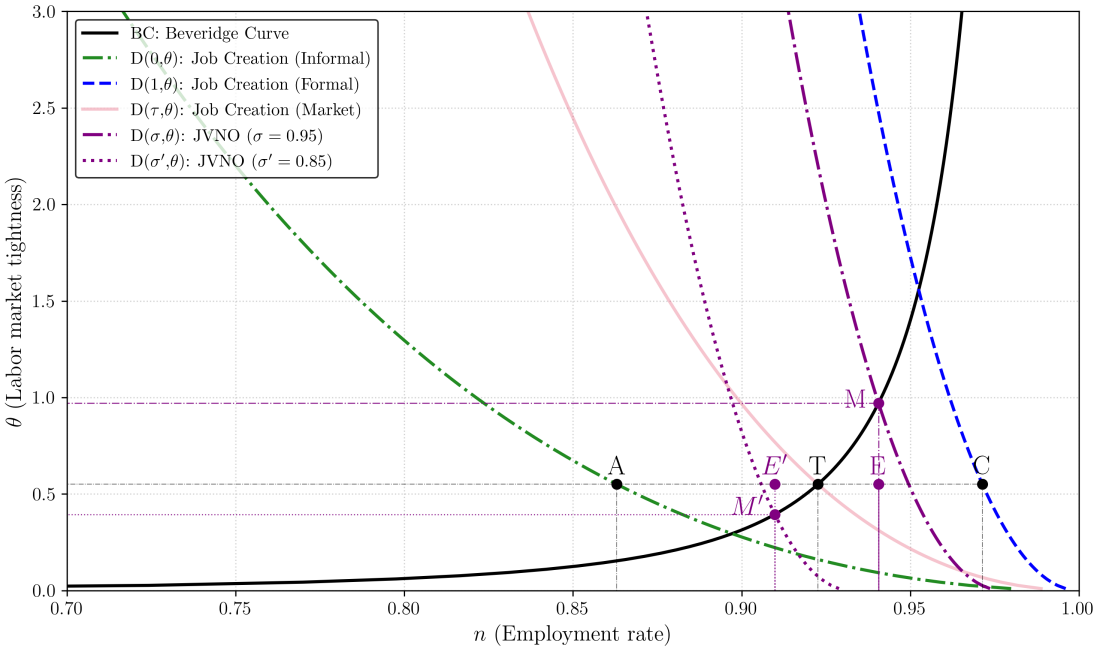
$$D(\tau, \theta) = \tau D(F, \theta) + (1-\tau) D(I, \theta). \tag{4}$$

[8]Formal hiring may also improve matching by increasing vacancy visibility and facilitating intermediation between firms and job seekers. To keep the model parsimonious, we abstract from these channels, and model it simply as a reduction in the vacancy marginal cost.

[9]Note that, under our assumptions, all firms weakly prefer informal hiring to not hiring, as wage is proportional to their productivity.



(A) Posting Formal or Informal



(B) Equilibrium Employment

Figure 2: Model: Posting Choices and Employment

Notes: Panel (a) illustrates firms' posting decision between the informal and formal sector as a function of firm productivity. Firms with productivity below the threshold $\hat{a}$ post informally, while more productive firms post formally. Panel (b) presents equilibrium in a search-and-matching framework. The black curve represents the Beveridge curve, while the green and blue curves denote job creation in the informal and formal sectors, respectively. The red curve shows the aggregate job creation schedule. The purple curves represent the JVNO policy under different values of the share of firms transitioning to the formal sector. Equilibrium points (A, C, T, E, M) correspond to intersections between the Beveridge curve and job creation schedules, illustrating how the policy shifts labor market tightness and employment.

Equilibrium is determined by the intersection between aggregate labor demand and the Beveridge curve:

$$n(\theta) = \frac{f(\theta)}{\lambda + \delta + f(\theta)}. \tag{5}$$

Interpretation of Figure 2. Panel (b) of Figure 2 illustrates the equilibrium. The downward-sloping curve is the Beveridge curve, while the upward-sloping curves represent job creation under different hiring technologies.

Points A and C represent the employment choices of informal and formal firms, respectively, conditional on the prevailing market tightness. For a given θ, informal firms choose employment at point A, determined by the intersection between the Beveridge curve and the informal job creation condition, while formal firms choose employment at point C, defined analogously using the formal job creation condition. Point T denotes the general equilibrium with a mix of formal and informal firms, where the aggregate job creation curve intersects the Beveridge curve.

The effect of the JVNO policy. The JVNO policy restricts informal hiring by mandating vacancy posting for certain firms, thereby increasing the share of firms using formal hiring. Let σ denote the share of previously informal firms that switch to formal hiring. Panel (b) shows that an increase in σ shifts the aggregate job creation curve outward. This generates three forces.

First, the *switching effect*: firms that move from informal to formal hiring face lower marginal hiring costs and increase vacancy posting and employment.

Second, the *congestion effect*: as vacancy posting increases, market tightness rises and the job-filling rate $q(\theta)$ declines. This reduces hiring efficiency, especially for firms already using formal hiring.

Third, the *exit effect*: some low-productivity firms may not find it profitable to incur the fixed cost of formal hiring and therefore stop hiring altogether.

The new equilibrium is represented by point M in Figure 2, where both increased labor demand and congestion effects are taken into account.

Aggregate employment effects. The overall impact of the policy on employment is theoretically ambiguous and depends on the extent of switching, captured by σ. When a large share of informal firms adopt formal hiring, the increase in labor demand dominates and employment rises.

When switching is limited or exit is substantial, congestion effects may offset these gains, leading to muted or even negative employment effects.

Empirical implications. The framework delivers three key predictions. First, vacancy posting increases, particularly among firms that previously relied on informal hiring. Second, effects are heterogeneous, with stronger responses among smaller and less structured firms. Third, increased posting activity generates congestion in the matching process, affecting mostly larger and formal hiring firms. Overall, the framework highlights that mandating vacancy posting affects labor markets not only by increasing transparency, but also by reshaping firms' hiring technologies and generating equilibrium spillovers through market tightness.

4 Data and Descriptive Statistics

We combine four administrative and quasi-administrative datasets to study the effects of the JVNO on vacancy posting, firm employment, worker-level hiring outcomes, and unemployment dynamics.

The first dataset is the near-universe of online job advertisements in Switzerland, collected and compiled by a private labor market analytics firm. Covering the period 2012–2024, the dataset includes on average nearly one million job ads per year. It has been shown to accurately reflect the Swiss labor market, capturing approximately 91.5% of all online job vacancies in 2017 (Stellenmarkt-Monitor Schweiz, 2018).[10] This dataset includes key firm-level identifiers, such as the firm's UID (unique identifier), name, size, and location. It also provides detailed vacancy characteristics, including occupation classifications at the 4-digit ISCO level, posting duration, the full text of the advertisement, and working-time quotas (such as full-time or part-time designations) and skill requirements. To construct the final sample, we retain only postings for which firm identifiers, occupation codes, and location information can be harmonized across datasets, and we focus on the period in which JVNO treatment can be measured consistently under a common occupational classification. We then aggregate postings to the occupation $\times$ canton $\times$ year-quarter level used in the empirical analysis. These restrictions are necessary both to link vacancies to administrative firm records and to define treatment exposure consistently around the policy threshold. Panel A of Table 1 reports summary statistics for the resulting market-level sample; Online Appendix F describes the sample construction in detail. On average, each cell contains 23.5 job postings from 13.2 firms, while the average number of first-time posting firms

[10]For more information on the vacancy dataset and its reliability, see Appendix B, as well as Colella (2022), Bannert et al. (2024), and Colella and Marcato (2024).

within a market is 4.1.

Table 1: Summary Statistics at the market level

	(1) N	(2) Mean	(3) (sd)	(4) p25	(5) Median	(6) p75
Panel A: Job Posting data (20-24)						
Number of postings	175,240	23.51	(101.69)	0.00	2.00	12.08
- Small	175,240	4.23	(22.46)	0.00	0.00	1.58
- Medium	175,240	7.60	(36.25)	0.00	0.06	3.50
- Large	175,240	11.68	(56.73)	0.00	0.33	5.50
- NA	175,240	0.00	(0.01)	0.00	0.00	0.00
Number of firms	175,240	13.19	(37.96)	0.00	2.00	10.00
- Small	175,240	2.74	(9.77)	0.00	0.00	2.00
- Medium	175,240	4.91	(15.74)	0.00	1.00	3.00
- Large	175,240	5.54	(15.11)	0.00	1.00	5.00
- NA	175,240	0.00	(0.01)	0.00	0.00	0.00
n. first-timers (absolute)	175,240	0.74	(2.87)	0.00	0.00	0.00
n. first-timers (occupation)	175,240	3.00	(8.42)	0.00	1.00	3.00
n. first-timers (market)	175,240	4.05	(10.34)	0.00	1.00	4.00
HHI	120,993	4254.61	(3475.04)	1243.07	3147.47	6810.46
Panel B: Unemployed Workers (20q1-24q2)						
Exits	157,716	2.64	(12.91)	0.00	0.00	1.00
Entries	157,716	4.97	(24.10)	0.00	0.00	2.00
Stock	157,716	12.24	(58.12)	0.00	1.00	6.00
Searchers	157,716	25.70	(125.69)	0.00	2.00	11.67
Exits/Searchers	108,358	0.10	(0.19)	0.00	0.00	0.14

Notes: This table reports summary statistics for the main variables used in the analysis at the market level. Each observation corresponds to a combination of occupation (4-digit ISCO), canton, and year-quarter. Panel A presents variables related to job postings and posting firms, including measures by firm size and indicators of first-time posting activity. Small firms are defined as those with 1–10 employees, medium firms with 11–100 employees, and large firms with more than 100 employees. The variables on first-time postings report the number of firms posting for the first time in absolute terms, within an occupation, or within a market. Panel B reports statistics on unemployment flows and stocks, including entries, exits, stock, searchers, and the share of exits over searchers. Entries refer to workers entering unemployment in a given canton and quarter who were previously employed in that occupation; exits refer to workers leaving unemployment from that occupation; the stock measures the number of unemployed workers who remain unemployed and were previously employed in that occupation; searchers denote the number of workers declaring to search for that occupation; and exits/searchers is the ratio of exits to searchers. The job postings data cover the period 2020q1–2024q4, while the unemployment data span 2020q1–2024q2.

The second dataset is the Swiss Firm Register (STATENT), which contains detailed information on all employers in Switzerland. The dataset covers the period 2020–2023 and is used to construct our firm-level exposure measure. We restrict the sample to to firms with stable industry classification and exclude the top 1% by baseline employment to ensure comparability and limit outliers. Panel A of Table 2 reports summary statistics for the resulting firm-level sample. On average, we

observe 345 thousand firms per year, with 7.63 workers per firm; female workers represent 44% of the workforce.

The Firm Register does not contain information on wages, job spells, or employee characteristics. We therefore complement it with two additional datasets: the Swiss Social Security Register (AVS) and the Swiss Population Registry (STATPOP). These datasets contain an individual identifier but lack a firm identifier. We therefore develop a procedure that allows us to assign a firm identifier to a subsample of workers in the AVS dataset. Online Appendix C describes the procedure in detail. After this matching procedure, we obtain a sample covering roughly 1 million workers per year, with on average 13.47 workers and 5 new hires per firm. Because of the matching procedure, this sample is not representative at the firm level and is tilted toward larger firms. As shown in Panel B of Table 2, average monthly wages are about CHF 5,000, and the probability that a new hire is still employed at the same firm after one and two years is 79% and 39%, respectively.

The fourth dataset is the Swiss Unemployment Register (AVAM), which contains monthly information on all registered unemployed individuals in Switzerland. It provides rich information on socio-demographic characteristics such as gender, nationality, age, and residence, as well as prior occupation, unemployment duration, job search activity, and the characteristics of the next job when available. Panel B of Table 1 reports summary statistics aggregated at the prior occupation $\times$ canton $\times$ year-quarter level. On average, we observe 4.97 entries into unemployment, 2.64 unemployment exits, and 25.70 searchers per cell.

Appendix A and Appendix B provide additional descriptive evidence on the relevance of the JVNO policy and the characteristics of the treated occupations. Figure A.7 shows that overall posting activity evolves smoothly over time. Panel (a) shows a steady increase in the number of posting firms over the period, with a notable decline in 2020, likely driven by the COVID-19 pandemic, and a more gradual decline in 2023–2024. Importantly, there are no abrupt changes around the introduction of the policy, suggesting that its implementation did not generate immediate distortions in overall job posting trends. Panel (b) shows the time series of the number of firms posting vacancies on the governmental platform Jobroom. The implementation of the JVNO appears to have significantly increased this number, underscoring the platform's growing relevance as a formal recruitment channel. Figure A.8 highlights substantial cross-cantonal heterogeneity in posting activity and in pre-policy exposure to treated occupations.

To provide an overview of the occupational coverage of the JVNO policy, Table B.1 shows that 38 out of all 4-digit ISCO occupations, or 11.3%, were treated at least once during the period 2020–2024. These treated occupations account for 21.5% of all job postings in Switzerland during this period. In contrast, the remaining occupations were never subject to JVNO requirements.

Table 2: Summary Statistics on Firm level data

	(1) N	(2) Mean	(3) (sd)	(4) p25	(5) Median	(6) p75
Panel A: Firm STATENT (2020–2023)						
Number of workers	1,380,351	7.63	(16.18)	2.00	3.00	7.00
- Female	1,380,351	3.33	(8.27)	1.00	1.00	3.00
- Male	1,380,351	4.31	(10.41)	1.00	2.00	4.00
Panel B: Firm STATENT-AVS (2020–2023)						
Number of workers	315,000	13.47	(22.56)	4.00	7.00	14.00
- Swiss	315,000	8.70	(16.92)	2.00	4.00	9.00
- New Non-Swiss	315,000	0.24	(1.29)	0.00	0.00	0.00
- Old Non-Swiss	315,000	3.28	(6.53)	0.00	1.00	4.00
Avg. monthly wages	315,000	4919.78	(4784.47)	3037.93	4403.78	5936.12
- Swiss	292,581	5066.75	(4258.02)	2987.09	4542.35	6279.36
- New Non-Swiss	42,200	4916.56	(5775.90)	2894.53	4100.00	5559.00
- Old Non-Swiss	231,836	4751.74	(5644.14)	2570.24	4186.28	5826.50
Number of New-Hires (NH)	315,000	5.00	(15.28)	0.00	2.00	5.00
- Swiss	315,000	2.84	(10.85)	0.00	1.00	3.00
- New Non-Swiss	315,000	0.26	(1.36)	0.00	0.00	0.00
- Old Non-Swiss	315,000	1.31	(4.15)	0.00	0.00	1.00
Avg. monthly wages NH	229,492	3742.42	(3930.90)	1967.50	3358.98	4885.77
- Swiss	183,726	3697.80	(3693.39)	1700.00	3254.60	5000.00
- New Non-Swiss	38,053	4773.87	(5337.94)	2784.18	4025.98	5454.00
- Old Non-Swiss	127,432	3944.36	(6523.15)	1781.42	3518.00	5200.00
n. NH emp. 1 year	315,000	3.97	(12.26)	0.00	1.00	4.00
- same firm	315,000	3.80	(11.92)	0.00	1.00	4.00
share NH emp. 1 year	229,492	0.83	(0.26)	0.71	1.00	1.00
- same firm	229,492	0.79	(0.28)	0.67	1.00	1.00
n. NH emp. 2 years	280,034	1.95	(8.01)	0.00	1.00	2.00
- same firm	280,034	1.45	(7.36)	0.00	0.00	1.00
share NH emp. 2 years	196,738	0.52	(0.39)	0.08	0.50	1.00
- same firm	196,738	0.39	(0.40)	0.00	0.33	0.73

Notes: This table reports summary statistics for the main firm-level variables used in the analysis. Panel A is based on STATENT data and covers the period 2020–2023, while Panel B uses the matched STATENT–AVS data over the same period. The unit of observation is a firm-year. Panel A presents employment measures, including the total number of workers and its breakdown by gender. Panel B reports firm-level outcomes on employment and wages, distinguishing between Swiss, new non-Swiss, and old non-Swiss workers. New non-Swiss are defined as foreign workers who enter Switzerland in a given year, while old non-Swiss are those already present in Switzerland. The table includes the number of workers, average monthly wages, the number of new hires, and the average monthly wages of new hires. It also reports measures of retention among new hires, both in levels and shares, distinguishing between workers still employed overall and those remaining with the same firm after one and two years.

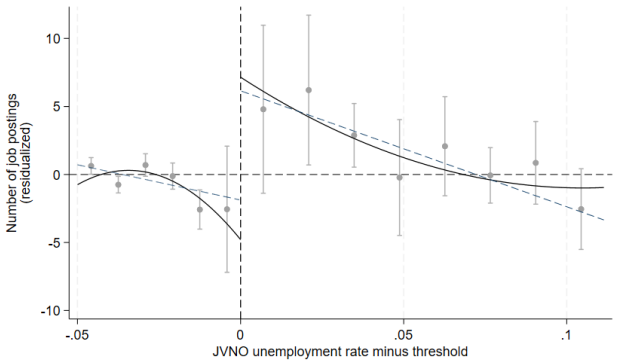
Table B.2 further shows how treated occupations are distributed across major ISCO groups. While most groups include at least some treated occupations, there are a few exceptions. For example, no occupations in Skilled Agricultural, Forestry, and Fishery Workers were ever treated. By contrast, Elementary Occupations were the most heavily exposed group: 80% of its 4-digit codes, accounting for 98.7% of employment in that group, were treated at least once. Service and Sales Workers and Craft and Related Trades also stand out, confirming that the policy mainly targeted lower-skill occupations with substantial labor market relevance.

5 Empirical Analysis

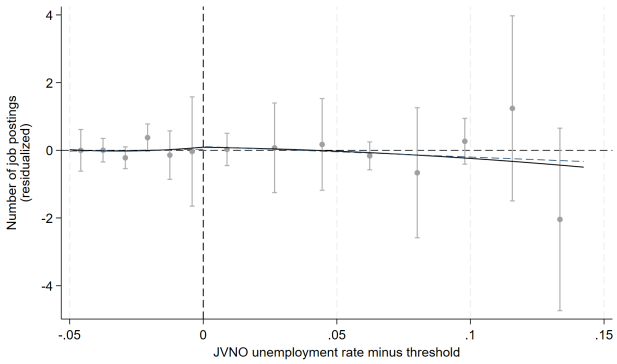
5.1 Effects on Job Postings

We begin by examining the effects of the JVNO policy on local labor demand, measured using job postings. Our unit of observation is a local labor market, defined as a combination of occupation (4-digit ISCO), canton (NUTS level 3), and year-quarter over the period 2020q1–2024q4. Before turning to the regression estimates, Figure 3 provides graphical evidence on the relationship between the JVNO policy and labor demand outcomes. Panels (a) and (c) plot the number of job postings and posting firms, respectively, against the JVNO-relevant unemployment rate net of the 5% threshold. In both cases, the figure shows a visible upward discontinuity at the cutoff, consistent with the interpretation that the policy increased formal labor demand in treated occupations. The increase appears both in the number of job postings and in the number of distinct posting firms. By contrast, Panels (b) and (d) report the same outcomes for the pre-policy period 2014q1-2016q4, when JVNO was not yet in place. In this placebo period, no comparable discontinuity is visible at the threshold. Taken together, these graphs provide suggestive evidence that the introduction of the JVNO policy led to an increase in vacancy posting activity rather than reflecting a spurious discontinuity mechanically associated with the unemployment threshold.

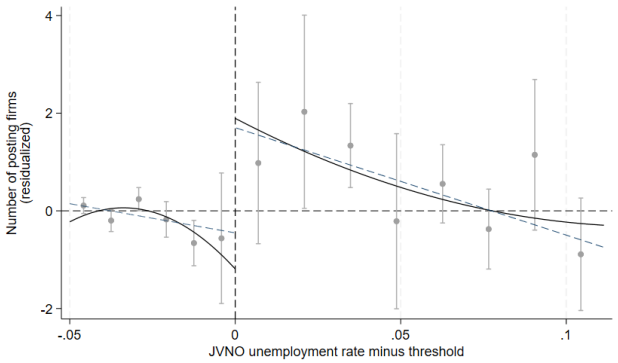
Building on the graphical evidence, we formally evaluate the impact of the JVNO policy on local labor demand using a regression discontinuity design. Our outcomes of interest are the number of job postings, the number of posting firms, the number of posting firms posting for the first-time, and labor market concentration, measured by the Herfindahl–Hirschman Index (HHI). All variables are constructed at the local labor market level, defined as the combination of an occupation (ISCO 4-digit), a canton, and a year-quarter. Our empirical strategy exploits the discontinuity generated by the policy rule, which assigns treatment to occupations with an unemployment rate above a given threshold. Intuitively, this approach compares markets that are similar in all respects except for whether they fall just above or just below the cutoff. Specifically, we estimate the following



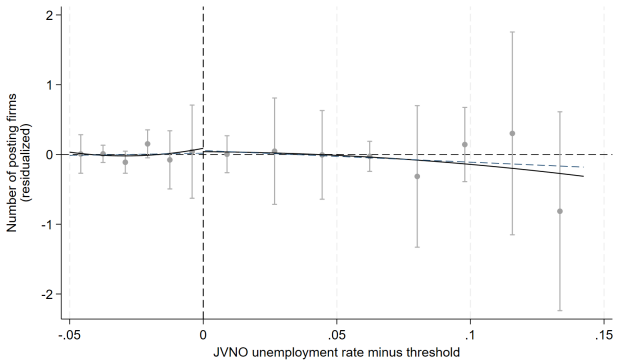
(A) Job Postings



(B) Placebo Job Postings (2014–2016)



(C) Posting Firms



(D) Placebo Posting Firms (2014–2016)

Figure 3: RDD Plots: Job Postings and Posting Firms

Notes: Panels (a) and (b) report results for job postings, while panels (c) and (d) report results for posting firms. The figure shows local means of the residualized outcomes, 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 equally spaced bins of the running variable, which assigns cells to JVNO treatment if it is positive. Each cell consists of a canton × occupation × year-quarter in the period 2020–2024. 95% confidence intervals (spikes) account for clustering at the canton level. The dashed lines denote linear fits and the solid curves quadratic fits of the outcome on the running variable, allowed to differ on each side of the cutoff. Sample: Job Postings dataset, period 2020–2024.

specification:

$$Y_{rot} = \beta TR_{ot} + \gamma_1(u_{ot} - u_{0,t}) + \delta_1 TR_{ot}(u_{ot} - u_{0,t}) + \gamma_2(u_{ot} - u_{0,t})^2 + \delta_2 TR_{ot}(u_{ot} - u_{0,t})^2 + \mu_o + \mu_r + \mu_t + \varepsilon_{rot} \tag{6}$$

where Y_{rot} denotes the outcome in occupation o, canton r, and time t; TR_{ot} is an indicator for whether the occupation is subject to the JVNO policy; u_{ot} is the occupation-specific unemployment rate; and $u_{0,t}$ is the policy threshold. The specification includes occupation, canton, and year-quarter fixed effects, which absorb persistent differences across markets and common time shocks. Our baseline specification allows for a quadratic polynomial in the running variable on both sides of the cutoff, although results are robust to linear specifications.

Table 3 reports the regression discontinuity estimates of the effect of the JVNO policy on labor demand outcomes. Panel A examines aggregate labor demand at the market level. Columns (1)–(4) report the effect of the policy on the inverse hyperbolic sine (IHS) transformation of the number of job postings and the number of posting firms, respectively. Columns (5)–(6) report the effect on labor market concentration, measured by the logarithm of the Herfindahl–Hirschman Index (HHI) computed from firms' vacancy shares within each market. For each outcome, we present estimates from both linear and quadratic specifications of the running variable on either side of the threshold. The estimates indicate a sizable and statistically significant increase in labor demand at the threshold. The number of job postings rises by approximately 12 to 17 percent, while the number of posting firms increases by about 6 to 14 percent, depending on the specification. These magnitudes suggest that the policy leads not only to more vacancies being posted, but also to a broader participation of firms in formal recruitment. Consistent with this interpretation, we observe a decline in labor market concentration: the HHI decreases by around 6 percent in the quadratic specification, indicating that the expansion in vacancy posting is driven by entry of new or previously inactive firms rather than by a disproportionate increase among already active employers. Panel B provides direct evidence on this entry margin by focusing on first-time posting firms. The dependent variable is the IHS transformation of the number of firms that post for the first time within a given market. We consider three alternative definitions of first-time posting. The first identifies firms that appear for the first time in the sample (excluding the initial JVNO period 2018–2019). The second defines first-time posting at the occupation level, capturing firms that have not previously posted in a given occupation. The third definition is at the market level, identifying firms that post for the first time in a specific occupation–canton pair. Across all definitions, the estimates show a positive and statistically significant increase in first-time posting firms, with effects ranging from approximately 8 to 16 percent. These results provide direct support for the mechanism highlighted in the conceptual framework: the JVNO

policy induces firms that previously relied on informal hiring channels to enter the formal vacancy posting market. Taken together, the evidence indicates that the increase in labor demand is driven not only by more intensive posting by existing firms, but also by the entry of firms into formal recruitment.

Table 3: Effects on labor demand outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Labor Demand Outcomes						
	Postings - IHS		Firms - IHS		HHI - log	
Treatment	0.118***	0.166***	0.057***	0.135***	-0.024	-0.062***
	(0.019)	(0.021)	(0.015)	(0.012)	(0.016)	(0.017)
MDV	1.812	1.812	1.805	1.805	7.881	7.881
N	175,240	175,240	175,240	175,240	120,992	120,992
R^2	0.795	0.795	0.854	0.854	0.744	0.744
Panel B: First-time Posting Firms						
	Absolute - IHS		Occupation - IHS		Occ. × Canton - IHS	
Treatment	0.120***	0.081***	0.119***	0.160***	0.100***	0.136***
	(0.019)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)
MDV	0.353	0.353	0.948	0.948	1.141	1.141
N	175,240	175,240	175,240	175,240	175,240	175,240
R^2	0.541	0.541	0.716	0.716	0.776	0.776
$(u-u_0)$ & $Tr \times (u-u_0)$	✓	✓	✓	✓	✓	✓
$(u-u_0)^2$ & $Tr \times (u-u_0)^2$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓

Notes: This table reports Regression Discontinuity estimates for β in equation 6. The unit of observation is occupation (4-digit ISCO) × canton × year-quarter. "Treatment" equals one if the occupation's unemployment rate exceeds the threshold (u_0). $(u-u_0)$ and $TR \times (u-u_0)$, as well as $(u-u_0)^2$ and $TR \times (u-u_0)^2$, denote linear and quadratic RDD terms. All regressions include canton, year-quarter, and occupation fixed effects. MDV reports the mean of the dependent variable. Robust standard errors (in parentheses) are clustered at the canton level. Sample: Job Postings dataset, 2020–2024. Panel A uses as dependent variables the inverse hyperbolic sine of job postings (cols. 1–2), posting firms (cols. 3–4), and log HHI (cols. 5–6). Panel B uses the inverse hyperbolic sine of the number of firms posting for the first time (2016–2017, 2020–2024), measured in absolute terms (cols. 1–2), by occupation (cols. 3–4), and by occupation × canton (cols. 5–6), excluding firms active in the respective category in 2016–2017. *p < 0.10, **p < 0.05, ***p < 0.01.

A key identifying assumption of the regression discontinuity design is the absence of manipulation of the running variable around the cutoff. In our context, manipulation would require either that workers can coordinate to affect occupation-level unemployment rates or that the Swiss State

Secretariat for Economic Affairs (SECO) strategically adjusts these rates to determine treatment status. Both scenarios are highly implausible. Nonetheless, we formally test for discontinuities in the density of the running variable using the McCrary density test (McCrary, 2007). The results, reported in Figure C.9, show no evidence of manipulation around the threshold, supporting the validity of our design. Another potential kind of manipulation is that employers may strategically respond to the policy by posting vacancies in treated occupations that are closely related to untreated ones, thereby exploiting the JVNO requirements without genuinely altering hiring behavior. To assess this possibility, we examine spillovers to non-treated occupations within the same 3-digit ISCO group as treated occupations. As shown in Table C.3, we find no evidence of such behavior: the estimated effects on related but untreated occupations are small and statistically insignificant across all outcomes. This suggests that our results are not driven by reclassification or strategic posting across closely related occupations.

Given the skewness of the outcome variables and the presence of zeros, we use the inverse hyperbolic sine (IHS) transformation, which behaves similarly to the logarithm while remaining defined at zero. This is particularly suitable in our regression discontinuity setting, where identification relies on local comparisons around the cutoff: the IHS transformation allows us to retain zero outcomes and reduces the influence of large markets that could otherwise dominate the estimates. To assess robustness to functional form, and following Chen and Roth (2024), we estimate alternative specifications: log-linear models (intensive margin), linear probability models (extensive margin), and PPML estimators. The results, reported in Table C.4, are consistent across specifications. Estimated effects remain positive and statistically significant, while the effects on the extensive margin are smaller and less precisely estimated.[11] Overall, the findings indicate that the increase in labor demand is primarily driven by higher posting intensity within markets, with a more limited contribution from entry at the aggregate level.

We further assess the robustness of our results through permutation and bandwidth sensitivity analyses. First, to address the concern that the estimates may reflect mean reversion rather than a causal effect, we implement permutation tests by assigning placebo thresholds at alternative unemployment rates and re-estimating the RDD specification. As shown in Figure C.10, the resulting estimates are centered around zero and far from the baseline estimate obtained at the true 5% cutoff, indicating that our findings are not driven by spurious threshold effects. Second, we examine sensitivity to the choice of bandwidth by restricting the sample to progressively narrower windows around the cutoff. Figure C.11 shows that the estimated effects remain stable across

[11] Importantly, since our outcomes are defined at the market level, this does not imply the absence of entry. Rather, it reflects that entry occurs primarily in smaller markets—where the number of postings or firms shifts from zero to a small positive value—and therefore contributes less to aggregate variation.

a wide range of bandwidths and closely align with the baseline specification. We also assess sensitivity to bandwidth selection using the optimal bandwidth procedure of Calonico et al. (2014, 2019). As shown in Table C.5, the estimates remain positive and statistically significant in the JVNO period, while placebo effects are negligible, reinforcing the robustness of our results.[12]

Finally, we explore heterogeneity in the effects of the JVNO policy by firm size. Figure 4 reports the estimated impact on the number of posting firms separately for small (10 or fewer employees), medium (11–100), and large (more than 100 employees) firms. The results reveal a clear gradient: the increase in posting firms is largest among small firms and declines monotonically with firm size. This pattern is consistent across both linear and quadratic specifications. These findings provide further support for the mechanism highlighted in the conceptual framework. Small firms, which are more likely to rely on informal hiring channels and face higher barriers to adopting formal recruitment practices, appear to benefit the most from the policy and are disproportionately induced to enter the formal vacancy posting market.

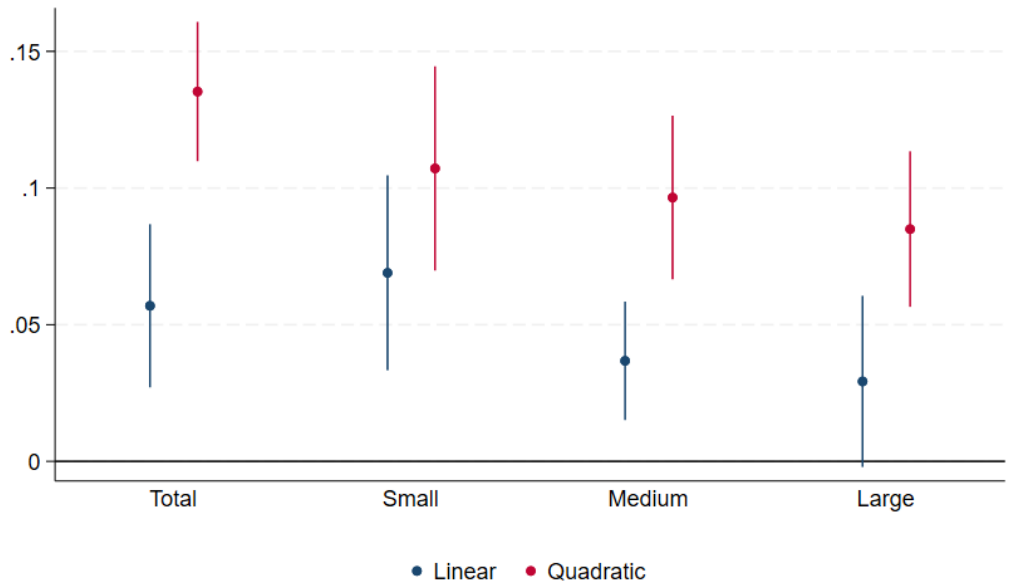


FIGURE 4: HETEROGENEOUS EFFECTS ON POSTING FIRMS BY FIRM SIZE

Notes: The figure presents the coefficients and 95% robust confidence intervals clustered at the Canton level from Regression Discontinuity (RD) estimates for β in equation 6, computed separately by firm size: Small (10 or fewer employees), Medium (11–100 employees), and Large (more than 100 employees). We estimate the model using both a linear fit (blue squares) and a quadratic fit (red circles) of the running variable before and after the cutoff. The figure reports results for the inverse hyperbolic sine (IHS) transformation of the number of posting firms. The variables are measured at the occupation–Canton–year-quarter level. All specifications include Canton, year-quarter, and occupation fixed effects. Sample: Job Postings dataset, period 2020–2024.

[12] As additional placebo exercise, we replicate the baseline RDD in the pre-policy period (2014–2016), finding small and statistically insignificant effects (Table C.6). We also apply the JVNO treatment and running variable from 2020–2024 to outcomes measured seven years earlier (2013–2017); the estimated discontinuities remain close to zero across bandwidths (Figure C.12)

Overall, the evidence from the job postings data indicates a clear and robust increase in formal labor demand following the introduction of the JVNO policy. Both the number of job postings and the number of posting firms rise discontinuously at the threshold, with effects that are particularly pronounced among small firms and stable across a wide range of specifications and identification checks. This pattern aligns with the mechanism outlined in the conceptual framework, whereby firms that previously relied on informal hiring are induced to adopt formal vacancy posting. However, an increase in posted vacancies does not necessarily imply a corresponding rise in realized employment. The observed effects may reflect a shift from informal to formal recruitment channels or a genuine expansion in hiring. Distinguishing between these channels is therefore crucial to assess the policy's overall impact. To this end, we next turn to firm-level data and examine whether exposure to the JVNO policy translates into changes in employment outcomes.

5.2 Firm-level effects on Employment and Wages

We have documented how the JVNO policy has affected labor demand by increasing both the number of posting firms and the number of vacancies, with the strongest effects among small and informal hiring firms. To assess whether these changes translate into broader firm-level outcomes, we construct a measure of firms' exposure to the policy. A key limitation of the data is that we do not observe the pre-policy occupational composition of employment at the firm level. This prevents us from directly measuring how intensively each firm is affected by the JVNO policy. To address this constraint, we adopt a shift-share approach and approximate firm-level exposure using industry-level variation in occupational composition. In particular, we combine each firm's industry classification with the pre-policy occupational structure of that industry, thereby assigning to each firm an exposure measure that varies across industries and over time.

Using data from the Structural Survey (SE), we estimate the occupational composition of each industry i during the pre-policy period (2012–2015). Let

$$s_{io} = \frac{Employment_{io}^{2012-2015}}{\sum_o Employment_{io}^{2012-2015}}$$

denote the share of workers employed in occupation o within industry i in the pre-policy period. These shares are fixed over time and therefore unaffected by the introduction of the JVNO policy. We then construct an industry-year exposure measure as the weighted share of treated occupations:

$$Exposure_{it} = \sum_o s_{io} \times Treatment_{ot},$$

where $Treatment_{ot}$ is an indicator equal to one if occupation o is subject to the JVNO policy in year t, and zero otherwise. This measure captures the extent to which firms operating in industry i are exposed to the policy in year t, based on their predicted occupational structure. Conceptually, this approach follows a shift-share design (Borusyak et al., 2025), where the "shares" are given by pre-policy occupational employment weights and the "shifts" correspond to the time-varying JVNO treatment across occupations. Identification relies on the interaction between these predetermined shares and exogenous variation in treatment across occupations over time.

However, in our setting the shifts are not strictly random, as treatment assignment is determined by occupation-specific unemployment rates. Following Borusyak et al. (2025), we therefore augment the specification with a control that captures differential exposure to these underlying labor market conditions. In particular, we construct an analogous shift-share measure using occupation-level unemployment rates, which absorbs variation driven by systematic differences in unemployment risk across industries.

In the empirical analysis, we assign to each firm the exposure of its corresponding industry and estimate models of the form:

$$Y_{it} = \alpha + \beta Exposure_{it} + \gamma UnemplExposure_{it} + \mu_i + \mu_t + \varepsilon_{it},$$

where Y_{it} denotes firm-level outcomes, μ_i and μ_t are firm and year fixed effects. The inclusion of firm fixed effects implies that identification relies on within-firm changes in exposure over time, driven by variation in the set of occupations subject to the JVNO policy. The analysis is conducted at the firm-year level over the period 2020–2023. Additional details on the construction of the exposure measures and robustness checks are provided in Appendix D.

Firm-level: full sample STATENT

We begin with the universe of firms from the STATENT registry over the period 2020–2023. Employment is measured at the firm (UID) level. Firm size groups are defined using a baseline measure of employment—2019 for incumbents and first observed employment for entrants—which is fixed over time and used only for classification. The outcome variable, instead, is time-varying and captures realized employment in each year. To ensure comparability, we restrict the sample to firms with a constant industry classification over time and exclude the top 1% of firms by baseline employment and those changing industry classification across the years. This yields a comprehensive sample spanning the full firm size distribution while limiting the influence of extreme outliers. Each firm is assigned an industry-level exposure measure capturing the intensity

with which it is affected by the JVNO policy. As described above, this measure follows a shift-share structure, combining pre-policy industry employment shares across occupations with the time-varying treatment status of those occupations.[13]

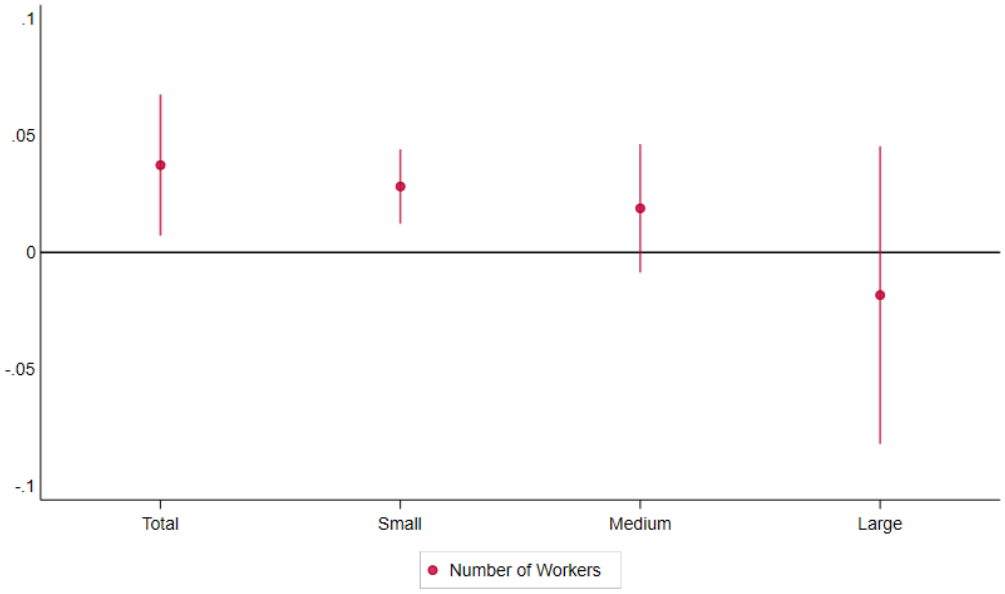


FIGURE 5: HETEROGENEOUS EFFECTS ON EMPLOYMENT BY FIRM SIZE

Notes: The figure presents the coefficients and 95% robust confidence intervals for the effect of the Industry Exposure measure (at the NOGA 3-digit level) on the inverse hyperbolic sine (IHS) transformation of the number of workers per firm size category. The exposure measure, defined in Appendix D, is constructed as the weighted sum of pre-policy industry-level employment shares in treated occupations for each year. Each marker represents a different estimate based on the sample: Total includes all firms with more than one worker, Small includes firms with 1–10 workers, Medium includes firms with 11–100 workers, and Large includes firms with more than 100 workers. The unit of observation is a firm × year. Samples: Pre-policy shares are constructed using the SE data from 2012 to 2015. Outcome variables are constructed using the STATENT data, period 2020–2023.

Figure 5 presents the estimated effects of exposure on firm-level employment, measured as the inverse hyperbolic sine of the number of workers, separately by firm size. The results reveal pronounced heterogeneity across the firm size distribution. Small firms (1–10 employees) experience a large and statistically significant increase in employment as exposure rises, while medium-sized firms exhibit more moderate effects. In contrast, the estimates for large firms are negative, yet not statistically significant. In terms of magnitude, moving from no exposure to full exposure is associated with an increase in employment of about 3.5 percent on average, with stronger effects for small firms (approximately +2.7 percent) and medium-sized firms (+1.9 percent), and a small negative effect for large firms (-1.8 percent). This pattern closely mirrors the evidence from job postings and is consistent with the mechanism outlined in the conceptual framework. Firms that

[13]The results are robust to alternative levels of industry aggregation. In particular, using NOGA 2-digit or NOGA 3-digit classifications yields virtually identical estimates; see Figure D.13 in the Appendix.

were previously more reliant on informal hiring, predominantly smaller firms, are those most affected by the policy and respond by expanding employment, while larger firms display negative or limited adjustments. Taken together, these findings indicate that the increase in vacancy posting documented in the previous section reflects a genuine expansion in employment rather than a mere reallocation of hiring activity, with effects concentrated among smaller firms.

Firm-level: matched sample STATENT–AVS

While the STATENT data provide comprehensive information on firm-level employment, they do not contain information on wages or worker-level outcomes. To study these dimensions, we complement the analysis using a matched dataset that links firms in STATENT to individual-level records from the social security (AVS) data. This allows us to examine not only employment dynamics, but also hiring patterns and wage outcomes at the firm level.[14]

Using the same industry-level exposure measure described above, we estimate the effect of JVNO exposure on firm-level outcomes in the matched sample. Panels A and B of Table 4 reports the effects on total employment and average wages. Consistent with the results obtained in the full STATENT sample, we find a positive and statistically significant effect of exposure on firm employment. In terms of magnitude, moving from no exposure to full exposure is associated with an increase in firm employment of approximately 1.6 percent.[15] This reinforces the interpretation that the increase in job postings reflects a genuine expansion in employment rather than a pure reallocation of hiring activity. Turning to wages, we find a positive and statistically significant effect of exposure on average firm-level wages. In terms of magnitude, moving from no exposure to full exposure is associated with an increase in wages of approximately 3 to 4 percent across most groups, while we find no significant effect for newly hired non-Swiss workers. This evidence suggests that the increase in labor demand induced by the JVNO policy is not limited to quantities, but also translates into higher compensation. This pattern is consistent with a setting in which firms expand hiring and, at the same time, face tighter labor market conditions that require offering higher wages to attract or retain workers.

To further investigate hiring dynamics, Panels C and D of Table 4 focuses on new hires. Panel C shows that exposure to the JVNO policy leads to a significant increase in the number of newly

[14] See Section 4 and Appendix C for details on the matching procedure and sample construction.

[15] The estimated effects are somewhat smaller than those obtained in the full STATENT sample. This difference likely reflects the composition of the matched sample, which under-represents smaller firms due to the difficulty of reliably linking them across datasets. Given that the employment effects of the JVNO policy are strongest among smaller firms, as shown in the previous subsection, this compositional difference can partly explain the attenuation in magnitude.

Table 4: Effects on Employment and Wages

	(1) Total	(2) Swiss	(3) Non-Swiss	(4) New Non-Swiss	(5) Old Non-Swiss
			All workers		
Panel A: Employment Effects					
Exposure	0.016**	-0.003	0.035***	0.021**	0.031***
	(0.008)	(0.009)	(0.011)	(0.009)	(0.011)
MDV	2.716	2.163	1.274	0.135	1.236
N	291,167	291,167	291,167	291,167	291,167
R^2	0.959	0.958	0.936	0.685	0.934
Panel B: Wage Effects					
Exposure	0.029***	0.032***	0.041***	0.010	0.042***
	(0.006)	(0.008)	(0.013)	(0.058)	(0.014)
MDV	8.326	8.330	8.161	8.297	8.161
N	291,167	269,362	208,766	23,772	206,710
R^2	0.936	0.916	0.900	0.747	0.900
			New Hires		
Panel C: New Hires, Employment Effects					
Exposure	0.066***	0.041**	0.040**	0.026***	0.030*
	(0.022)	(0.020)	(0.018)	(0.010)	(0.018)
MDV	1.357	0.938	0.617	0.142	0.544
N	291,167	291,167	291,167	291,167	291,167
R^2	0.778	0.753	0.735	0.675	0.702
Panel D: New Hires, Wage Effects					
Exposure	0.037	0.038	-0.025	0.001	-0.025
	(0.023)	(0.031)	(0.037)	(0.064)	(0.040)
MDV	7.947	7.893	7.990	8.269	7.946
N	191,826	143,683	96,465	20,447	86,779
R^2	0.682	0.661	0.676	0.744	0.666
NOGA3 un.rate	✓	✓	✓	✓	✓
Employer FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Notes: This table reports the effect of the industry exposure measure on employment (Panel A) and wages (Panel B) for all workers, and focusing only on new hires, i.e. workers hired by the firm in the given year (Panels C and D). Wages are defined as the firm-level average of workers', or new hires', monthly wages. The exposure variable is defined as the weighted sum of pre-policy industry-level employment shares in treated occupations for each year. The analysis is based on the matched STATENT-AVS sample (see Appendix). The unit of observation is a firm × year, over the period 2020–2023. Columns distinguish workers by nationality: Swiss refers to individuals with Swiss nationality; Non-Swiss refers to foreign workers; New Non-Swiss are foreign workers entering Switzerland in the given year; Old Non-Swiss are foreign workers already present in Switzerland. All specifications include employer and year fixed effects and control for the NOGA 3-digit JVNO-related unemployment rate. MDV reports the mean of the dependent variable. Robust standard errors (in parentheses) are clustered at the firm level. *p < 0.10, **p < 0.05, ***p < 0.01.

hired workers. In terms of magnitude, moving from no exposure to full exposure is associated with an increase of about 6 to 7 percent in total new hires, with comparable effects for Swiss and non-Swiss workers and somewhat smaller, though still positive, effects for newly arrived non-Swiss workers. These results indicate that the employment effects documented above are driven by active hiring at the firm level, rather than a possible reduction in the separation of incumbent workers. Panel D reports the corresponding effects on the wages of new hires. The point estimates are generally similar in magnitude to those obtained for average firm-level wages, but they are not statistically significant. This should be interpreted with caution, as the sample of newly hired workers is substantially smaller than total firm employment, which reduces statistical power and makes it harder to precisely estimate wage effects for this subgroup. At the same time, the absence of clearly significant wage increases for new hires is consistent with firms being able to draw on a broader and more elastic pool of labor when expanding hiring.

Figure 6 provides additional evidence on the persistence and quality of these hires. The figure reports the effects on both the number and the share of new hires who remain employed with the firm after one and two years, distinguishing between overall retention ("General") and retention within the same firm ("Same Firm"). The results show that exposure to the JVNO policy leads to a sizable increase in the number of retained hires: moving from no exposure to full exposure increases the number of newly hired workers still employed after one year by about 6.5 percent, and by around 5 percent after two years. By contrast, the effects on retention shares are positive but small and statistically non-significant. Taken together, these findings suggest that the policy increased hiring without adversely affecting match quality. The additional hires are not disproportionately short-lived, indicating that the expansion in employment is not driven by temporary or lower-quality matches, but reflects stable employment relationships.

Taken together, the evidence from the matched STATENT–AVS data confirms that the increase in vacancy posting induced by the JVNO policy translates into a genuine expansion in firm-level employment. Firms exposed to the policy hire more workers, particularly through increased inflows of new hires, and these additional matches persist over time, indicating no deterioration in match quality. At the same time, we document positive wage effects, suggesting that the increase in labor demand is sufficiently strong to exert upward pressure on wages. These findings are closely aligned with the predictions of the conceptual framework. The policy induces firms that were previously relying on informal hiring channels to transition toward formal recruitment, lowering marginal hiring costs and increasing labor demand. This leads to higher employment, driven by active hiring, and generates equilibrium effects through tighter labor market conditions, which are reflected in higher wages. Importantly, the absence of negative effects on retention indicates that the expansion in hiring does not come at the cost of lower-quality matches. Overall, the evidence

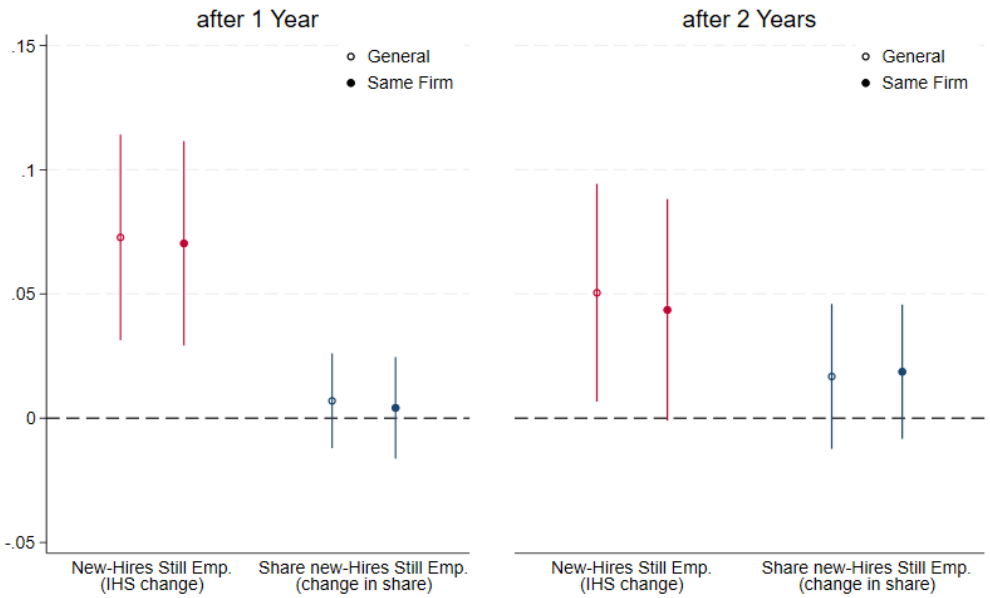


FIGURE 6: MATCH QUALITY

Notes: The figure reports coefficient estimates and 95% confidence intervals from regressions using the same sample and specification as in the baseline analysis. The dependent variables capture the persistence of newly hired workers. "New-Hires Still Emp." is defined as the inverse hyperbolic sine (IHS) of the number of workers hired by the firm in a given year who remain employed either in the same firm ("Same Firm") or in any firm ("General") at the end of that year (left panel) or two years later (right panel). "Share New-Hires Still Emp." is defined as the share of newly hired workers who remain employed (in the same firm or in general) at the end of the year (left panel) or two years later (right panel), relative to the total number of hires in that firm-year. Markers distinguish outcomes for "General" and "Same Firm," and vertical bars denote 95% confidence intervals. Robust standard errors are clustered at the firm level.

supports a view of the JVNO policy as reducing frictions in the hiring process and expanding effective labor demand, rather than simply reshuffling workers across firms or occupations.

5.3 Effects on Unemployed Workers

Thus far, the analysis has examined the demand side of the labor market, through both job postings and firm-level outcomes, showing that the JVNO policy increases vacancy posting and employment. We now turn to the supply side and study how unemployed workers respond to the policy. Because we observe the occupation of job seekers, either their previous occupation, their desired occupation, or the occupation in which they find employment, we can implement the same empirical framework used for job postings. Specifically, we aggregate outcomes at the local labor market level, defined as the combination of occupation (ISCO-4d), canton, and year-quarter. The analysis covers the period from 2020q1 to 2024q2 using administrative data from the AVAM register of unemployed individuals.

From these data, we construct five outcomes that capture different margins of labor supply adjustment: (i) *Exits*, the number of unemployed individuals leaving unemployment in a given occupation–canton–quarter; (ii) *Entries*, the number of individuals entering unemployment from a given occupation; (iii) *Searchers*, the number of unemployed actively searching for a job in a given occupation; (iv) *Stock*, the total number of unemployed individuals associated with a given occupation, defined based on their last observed occupation and not restricted to those entering unemployment in that specific quarter; and (v) *Exits/Searchers*, the ratio of exits to searchers, capturing an occupation-specific job-finding rate. All outcome variables are transformed using the inverse hyperbolic sine (IHS), as in the job postings analysis, to account for skewness and the presence of zero values. We estimate the same regression discontinuity specification as in Equation 6, exploiting the threshold in the unemployment rate that determines JVNO treatment. Table 5 reports the results using the quadratic specification of the running variable and including occupation, canton, and year-quarter fixed effects. The results point to a clear improvement in labor market outcomes for unemployed workers in treated occupations. The number of exits from unemployment increases by about 4.5 percent, while entries into unemployment decline by roughly 3 percent. Consistent with these patterns, the job-finding rate (exits over searchers) rises by approximately 9 percent. By contrast, we find no significant effect on the number of searchers or on the total stock of unemployed workers.

Taken together, these findings suggest that the JVNO policy improves matching efficiency rather than primarily affecting labor supply participation. The increase in vacancy posting and firm-level employment documented in the previous sections translates into higher job-finding rates

Table 5: Effects on Unemployed workers

	(1)	(2)	(3)	(4)	(5)
	Exits	Entries	Searchers	Stock	Exits/Searchers
Treatment	0.046***	-0.032**	-0.003	-0.010	0.092*
	(0.015)	(0.013)	(0.016)	(0.022)	(0.045)
$(u-u_0)$ & $Tr \times (u-u_0)$	✓	✓	✓	✓	✓
$(u-u_0)^2$ & $Tr \times (u-u_0)^2$	✓	✓	✓	✓	✓
Canton	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓
MDV	0.628	0.895	1.881	1.367	1.603
N	157,716	157,716	157,716	157,716	108,358
R^2	0.655	0.721	0.832	0.772	0.315

Notes: This table presents the Regression Discontinuity (RD) estimates for β in Equation 6, evaluating the impact of the JVNO policy on unemployment-related outcomes. The dependent variables are the inverse hyperbolic sine (IHS) transformations of the number of unemployment *Exits*, the number of *Entries* into unemployment, the number of *Searchers*, the number of unemployed workers in *Stock*, and the *share of exits over searchers*, measured at the occupation (4-digit ISCO)–Canton–year-quarter level. The stock variable captures the number of unemployed workers who remain unemployed and who entered unemployment through that occupation. The key independent variable, "Treatment", is a dummy variable equal to 1 if, in a given year-quarter, the occupation was treated by the JVNO policy—that is, its unemployment rate exceeded the threshold (u_0). The terms $(u-u_0)$ and $TR \times (u-u_0)$ refer to the linear running variable and its interaction with treatment, while $(u-u_0)^2$ and $TR \times (u-u_0)^2$ capture the quadratic specification. All regressions include Canton, year-quarter, and occupation fixed effects. MDV indicates the mean of the dependent variable. Robust standard errors clustered at the Canton level are reported in parentheses. Sample: AVAM dataset, period 2020q1–2024q2. *p < 0.10, **p < 0.05, ***p < 0.01.

and lower inflows into unemployment, without inducing a significant change in the number of individuals actively searching for jobs. This pattern is consistent with a reduction in search frictions and improved job matching, as well as with the mechanism in the conceptual framework whereby increased labor demand raises market tightness and increase the job-finding rate of the unemployed workers.

6 Conclusion

This paper studies the labor market effects of mandating vacancy posting, using the Swiss Job Vacancy Notification Obligation (JVNO) as a quasi-experimental setting. The policy induces a substantial increase in vacancy postings and firm participation in formal hiring, particularly among small firms and firms previously inactive in online recruitment. Importantly, these changes are not limited to reporting behavior: we document meaningful increases in employment, wages, and hiring, alongside higher job-finding rates for job seekers in covered occupations. These results indicate that the policy improves matching efficiency by expanding access to job opportunities and increasing effective labor demand.

Our findings highlight the role of hiring practices as a source of labor market frictions. By shifting firms from informal to formal recruitment channels, the JVNO possibly broadens the pool of applicants and facilitates more productive matches. The positive effects on both employment and wages suggest that the policy does not operate through lower-quality matches or wage compression, but rather through improved allocation. At the same time, the effects are concentrated among smaller firms, while large firms show limited responses, consistent with diminishing returns to formal posting or increased competition due to small firms posting vacancies as well.

More broadly, the results point to the importance of demand-side policies in shaping labor market outcomes. While much of the existing literature focuses on interventions targeting job seekers, our evidence shows that policies affecting firms' hiring behavior can play a central role in improving matching efficiency. An important avenue for future research is to better understand the welfare implications of such policies, including their costs for firms and their distributional effects across workers.

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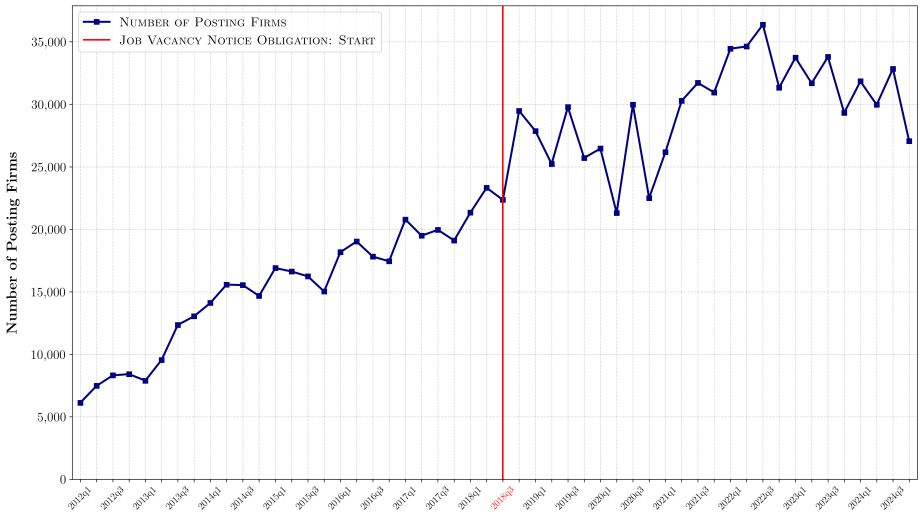
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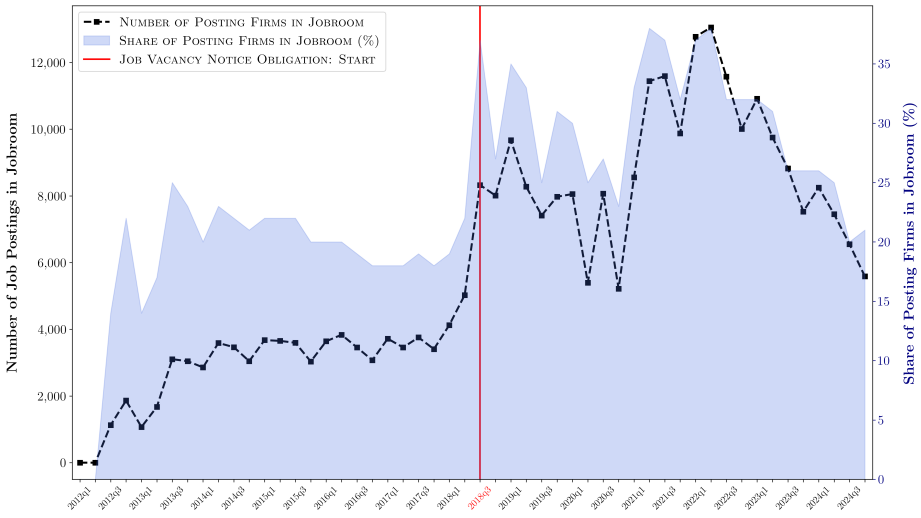
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Appendix

Appendix A: Distribution of Job Postings



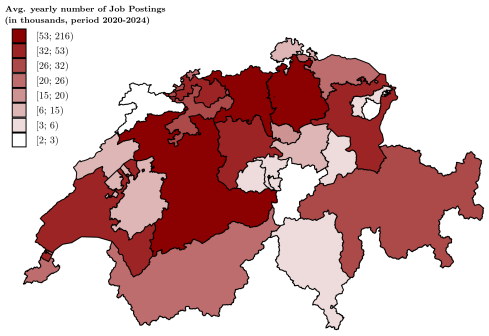
(A) Number of Posting Firms over the year-quarters



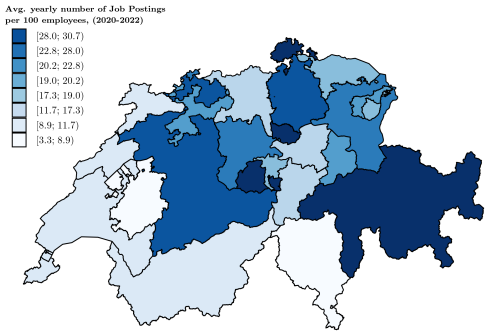
(B) Number of Posting Firms in Jobroom

Figure A.7: Job Postings data

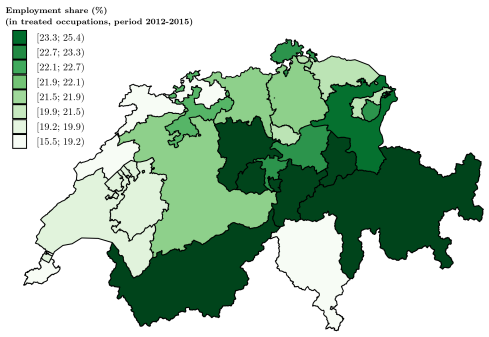
Notes: Panel (A) plots the total number of posting firms over year-quarters. Panel (B) reports the number of posting firms that publish at least one vacancy on Jobroom, together with their share relative to the total number of posting firms. In Panel (B), the line (left axis) shows the absolute number of firms, while the shaded area (right axis) shows their share. The vertical red line at 2018q3 highlights the start of the JVNO policy.



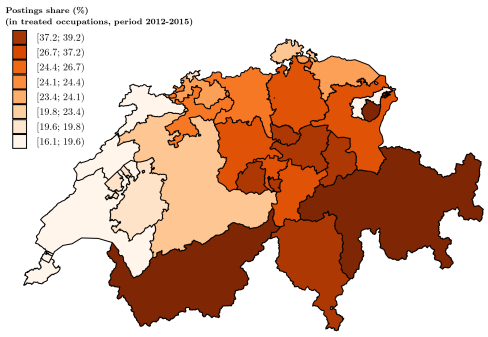
(A) Job Postings



(B) Job Postings per 100 employees



(C) Employment in treated occupations



(D) Job Postings in treated occupations

Figure A.8: Number of Job Postings per Canton

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 2020–2024. Panel (b) presents the average yearly number of job postings per 100 employees for the same period, the number of employees is computed using the Social Security data (AVS) and computing the yearly average number of employees in the period 2020-2023. Panel (c) depicts the percentage of employees working in occupations treated at least once by the JVNO policy – computed using the Structural Survey (SE). These percentages are calculated based on the pre-policy period (2012–2015). 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 (2012–2015).

Appendix B: Distribution of JVNO-treated occupations

Table B.1: Distribution of the JVNO-treated occupations

	ISCO 4d		Job Postings	
Group	Distinct	Percent	Number	Percent
Treated at least one time	38	11.31%	877,093	21.45%
Treated one time	4	1.19%	303,829	7.43%
Treated two time	7	2.08%	168,342	4.12%
Treated three time	5	1.49%	175,439	4.29%
Treated four time	5	1.49%	122,701	3.00%
Treated five time	17	5.06%	106,782	2.61%
Never treated	298	88.69%	3,211,349	78.55%

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 2020–2024.

Table B.2: Protected occupations by Major group (ISCO 1digit)

	Treated Percentage (%)	
ISCO 1d description	ISCO 4d	Employment
Managers	3.85%	11.87%
Professionals	4.60%	7.94%
Technicians and Associate Professionals	1.49%	5.63%
Clerical Support Workers	24.00%	8.77%
Service and Sales Workers	12.90%	57.12%
Skilled Agricultural, Forestry and Fishery Workers	0.00%	0.00%
Craft and Related Trades	16.67%	16.74%
Plant and Machine Operators, and Assemblers	4.55%	29.69%
Elementary Occupations	80.00%	98.67%

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 2020–2024. The column labeled "Employment" shows the share of workers employed in these treated 4-digit occupations within each 1-digit occupation group, calculated using the Structural Survey (SE) on the pre-JVNO period (2012–2015).

Appendix C: RDD, additional evidence

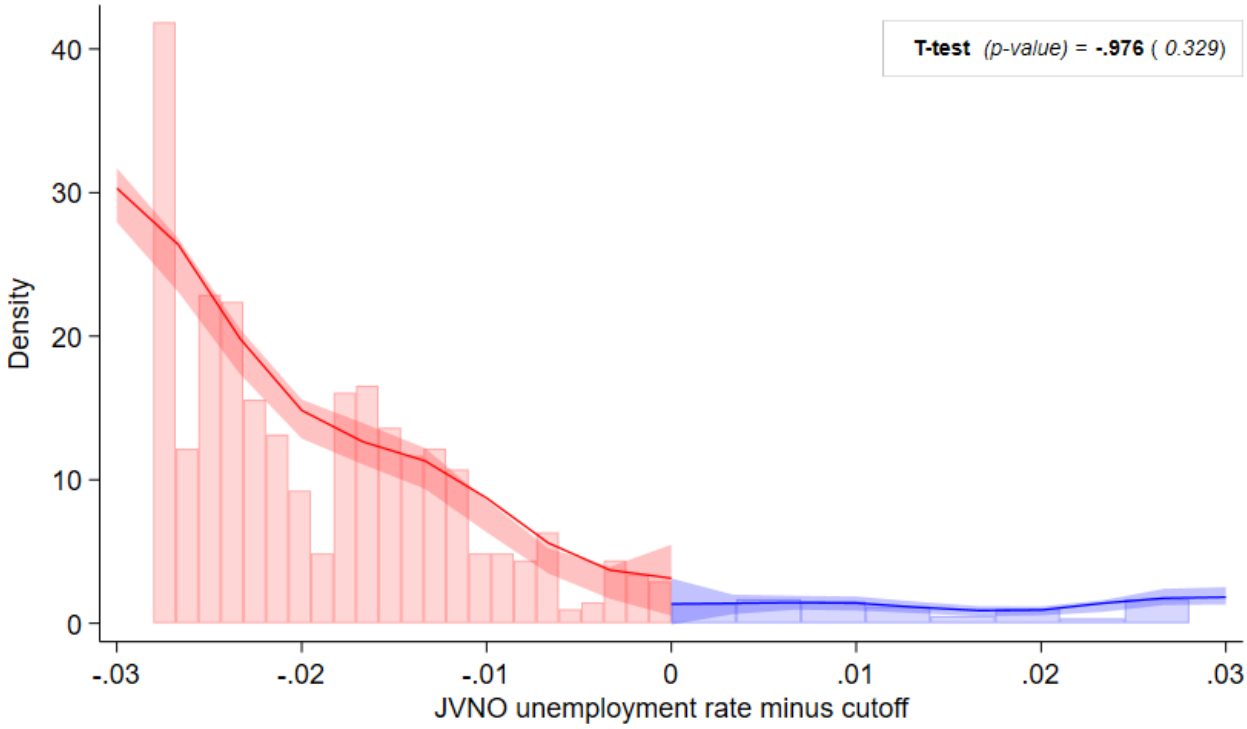


FIGURE C.9: MANIPULATION TEST FOR SORTING INTO TREATMENT

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 0.329. Sample: Job Postings dataset, period 2020-2024.

Table C.3: Spillovers or Manipulation on related occupations

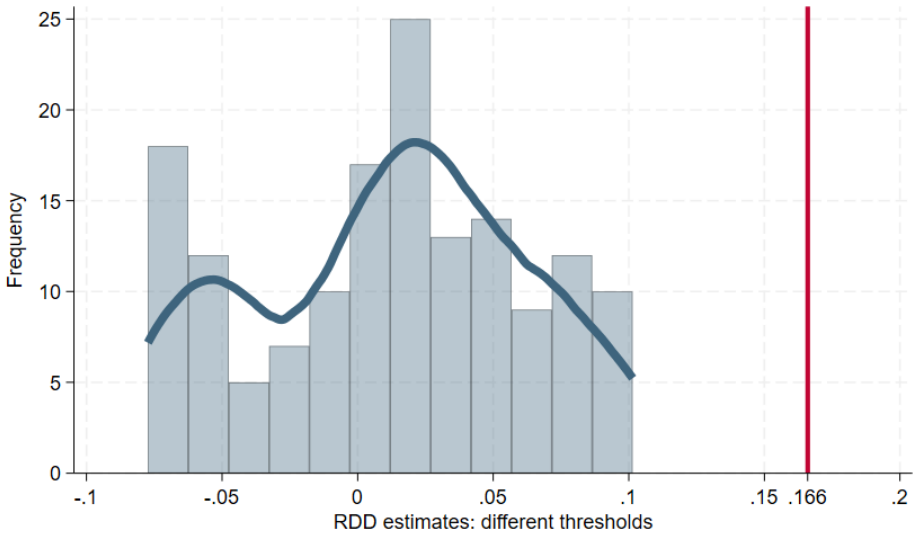
	Postings - IHS		Firms - IHS		HHI - log	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatm. related	-0.007	-0.013	-0.003	-0.007	0.004	0.007
	(0.012)	(0.013)	(0.008)	(0.009)	(0.015)	(0.015)
Excl. Treated	✓	✓	✓	✓	✓	✓
$(u - u_0)$ & $Tr \times (u - u_0)$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	1.800	1.800	1.793	1.793	7.899	7.899
N	160,888	160,888	160,888	160,888	110,838	110,838
R^2	0.793	0.793	0.854	0.854	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 2020-2024. *p < 0.10, **p < 0.05, ***p < 0.01.

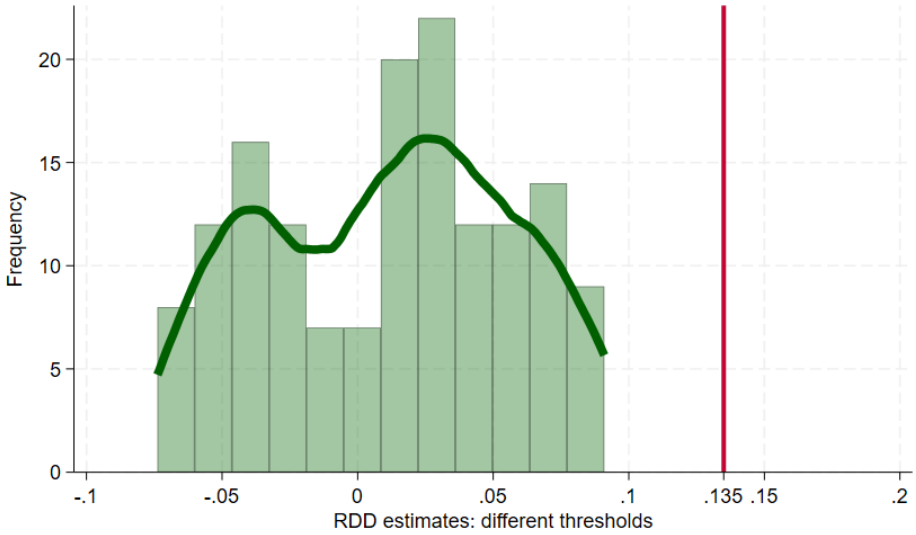
Table C.4: RDD robustness to functional forms

	(1)	(2)	(3)	(4)	(5)
Panel A: Job Postings					
	IHS	PPML	Dummy	Log	IHS × 100
Treatment	0.166***	0.175***	0.017*	0.187***	0.270***
	(0.021)	(0.019)	(0.009)	(0.036)	(0.046)
MDV	1.812	23.584	0.690	1.705	4.836
N	175240	174720	175240	120992	175240
R^2	0.795	0.887	0.550	0.721	0.747
Panel B: Posting Firms					
Treatment	0.135***	0.087***	0.017*	0.124***	0.214***
	(0.012)	(0.008)	(0.009)	(0.019)	(0.045)
MDV	1.805	13.233	0.690	1.876	4.954
N	175240	174720	175240	120992	175240
R^2	0.854	0.878	0.550	0.836	0.738
$(u-u_0)$ & $Tr \times (u-u_0)$	✓	✓	✓	✓	✓
$(u-u_0)^2$ & $Tr \times (u-u_0)^2$	✓	✓	✓	✓	✓
Canton	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓

Notes: This table reports robustness checks on the functional form of the outcome variable, following (Chen and Roth, 2024). Columns compare estimates using the inverse hyperbolic sine (IHS), Poisson pseudo-maximum likelihood (PPML), a binary indicator for positive outcomes, the logarithm (excluding zeros), and a rescaled IHS transformation (IHS × 100). The exercise assesses the sensitivity of the results to alternative treatments of zeros and scale dependence in the IHS specification. Panel A reports results for job postings, while Panel B reports results for posting firms. All specifications include linear and quadratic terms of the running variable, as well as canton, occupation, and year-quarter fixed effects. Standard errors are clustered at the canton level. Sample: Job Postings dataset, period 2020–2024. *p < 0.10, **p < 0.05, ***p < 0.01.



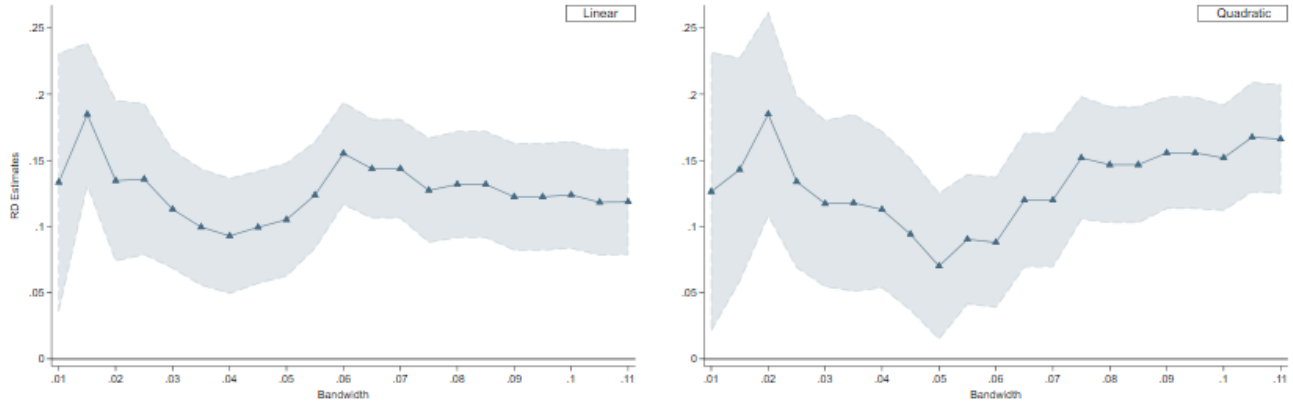
(A) Job Postings (IHS)



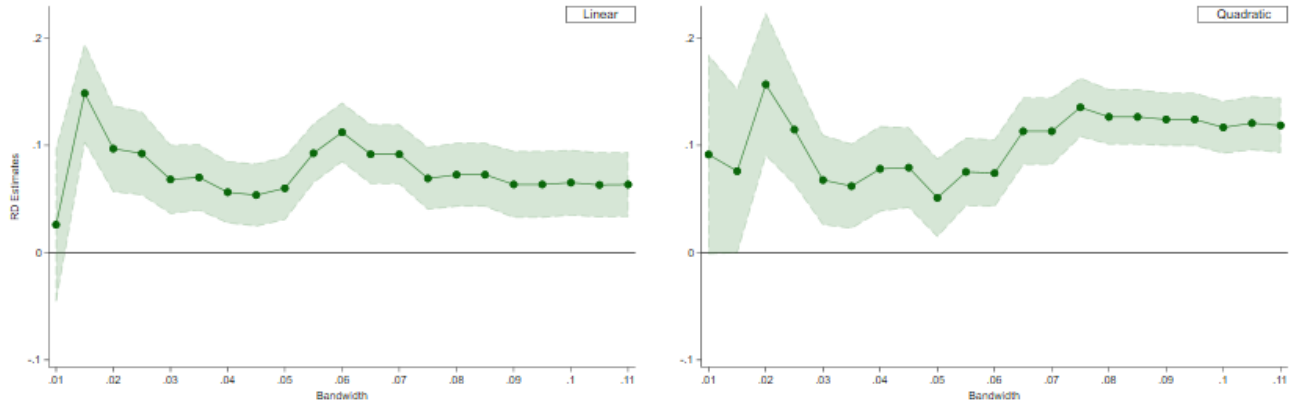
(B) Posting Firms (IHS)

Figure C.10: Permutation of the JVNO Threshold

Notes: The figure illustrates permutation tests assessing the sensitivity of the JVNO policy's effects to alternative unemployment rate cutoffs. Incorrect thresholds are considered in increments of 0.02, ranging from 1 to 3 percentage points and from 7 to 8 percentage points. For each cutoff, RD estimates are obtained using the same specification as in Table 3. Panel (a) reports results for the inverse hyperbolic sine (IHS) of job postings, while Panel (b) reports results for the IHS of posting firms. The bars represent the histogram of the estimated coefficients, and the curve shows the corresponding kernel density. The vertical red line indicates the estimate obtained using the true JVNO threshold of 5 percentage points. All specifications include linear and quadratic terms of the running variable, as well as canton, year-quarter, and occupation fixed effects. Sample: Job Postings dataset, period 2020–2024.



(A) IHS - NUMBER OF JOB POSTINGS



(B) IHS - NUMBER OF POSTING FIRMS

FIGURE C.11: EFFECTS OF JVNO POLICY ON JOB POSTINGS AND POSTING FIRMS: ROBUSTNESS TO DIFFERENT BANDWIDTHS

Notes: The figure plots discontinuity estimates for the effect of JVNO-treated occupations on the inverse hyperbolic sine (IHS) of the number of job postings (Panel a) and posting firms (Panel b) for different bandwidths and polynomial specifications. Bandwidth windows range from ± 0.01 to ± 0.11 around the cutoff of 0.05, using local linear (left) and local quadratic (right) versions of equation 6. All regressions use triangular kernel weights and include canton, occupation, and year-quarter fixed effects. 95% confidence intervals (dashed lines) are clustered at the canton level. Sample: Job Postings dataset, period 2020–2024.

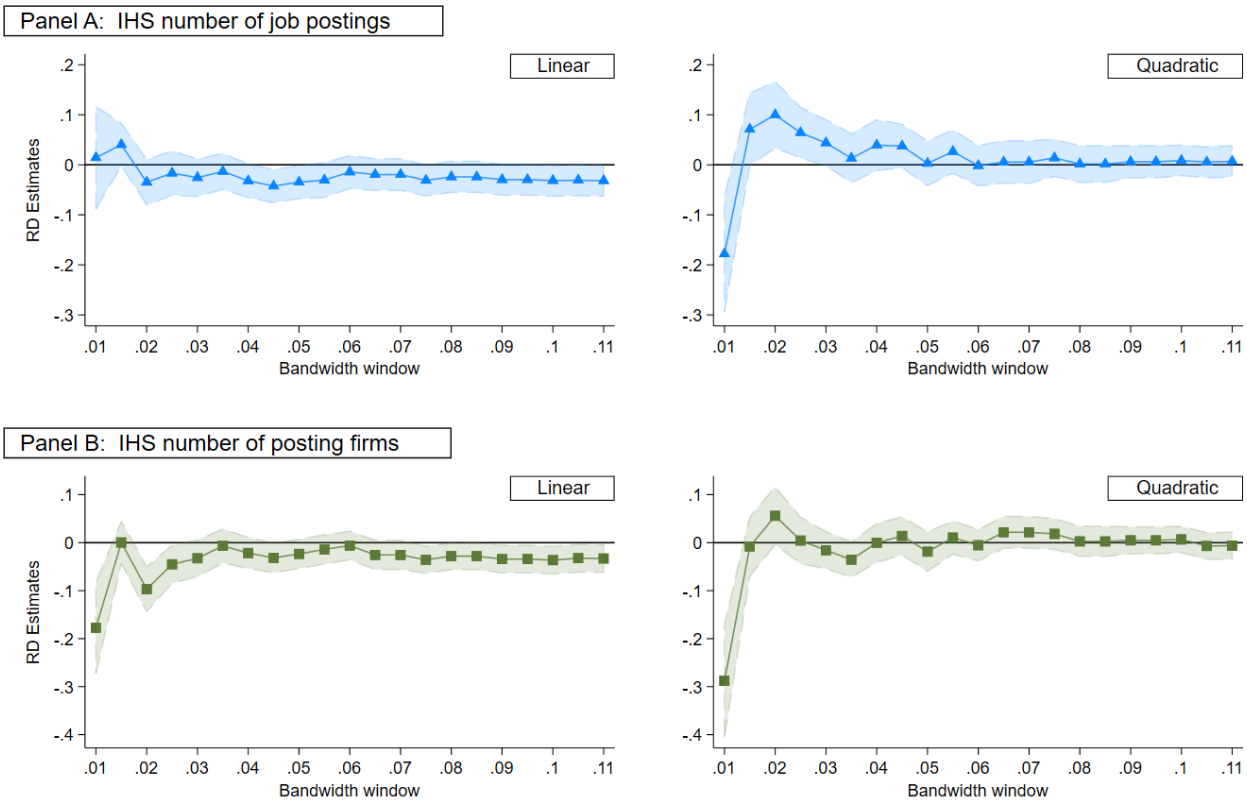


FIGURE C.12: PLACEBO OF JVNO POLICY ON JOB POSTINGS AND POSTING FIRMS: ROBUSTNESS TO DIFFERENT BANDWIDTHS

The Figure plots discontinuity estimates for the effect of JVNO treated occupation in the inverse hyperbolic sine transformation (IHS) of the number of job postings (Panel A) and of the number of posting firms (Panel B) for different bandwidths and polynomials. Bandwidth windows range from ± 0.01 to ± 0.11 deviations from the cutoff 0.05 in local linear (left) and local quadratic (right) specifications of equation 6. All regressions use triangular kernel weights and include canton, occupation, and year-quarter fixed effects. The treatment corresponds to the period 2020-2024 and is imputed to outcome variables computed for the period 2013-2017. 95% (dashed lines) confidence intervals account for clustering at the cantonal level. Sample: Job Postings dataset. Outcome: period 2013-2017, Treatment: period 2020-2024.

Table C.5: RD Robust Estimates

	JVNO 20–24		Placebo 14–16	
	(1) Level	(2) IHS	(3) Level	(4) IHS
Treatment	11.555**	0.089**	-0.294	-0.003
	(5.517)	(0.035)	(1.027)	(0.023)
Robust p-value	0.069	0.012	0.788	0.957
Bandwidth	0.021	0.012	0.023	0.014
Effective Obs. Left	29,328	9,568	32,656	12,168
Effective Obs. Right	4,472	3,016	10,608	9,152
N	175,240	175,240	140,192	140,192

Notes: The table presents results from local linear regressions examining the effect of the JVNO policy on the number of job postings. Columns (1) and (2) report results for the JVNO period (2020–2024), while Columns (3) and (4) report placebo estimates using pre-policy data (2014–2016). Columns (1) and (3) use the number of job postings as the outcome variable, while Columns (2) and (4) use the inverse hyperbolic sine (IHS) transformation of job postings. All specifications use residualized outcomes, net of canton, occupation, and year fixed effects. Estimates are obtained using the RD robust procedure of (Calonico et al., 2014). The running variable is the JVNO-relevant unemployment rate minus the treatment threshold, with treatment assigned to values above zero. The bandwidths are selected using MSE-optimal criteria, and robust p-values are based on bias-adjusted estimates. Samples: Job Postings dataset, 2020–2024 (JVNO period) and 2012–2015 (placebo). *p < 0.10, **p < 0.05, ***p < 0.01.

Table C.6: Placebo Effects on labor demand outcomes

	Postings - IHS		Firms - IHS		HHI - IHS	
	(1)	(2)	(3)	(4)	(5)	(6)
Fake Treatm.	0.033	0.029	0.011	0.003	0.020	0.044
	(0.025)	(0.027)	(0.018)	(0.020)	(0.026)	(0.027)
$(u-u_0)$ & $Tr \times (u-u_0)$	✓	✓	✓	✓	✓	✓
$(u-u_0)^2$ & $Tr \times (u-u_0)^2$		✓		✓		✓
Canton	✓	✓	✓	✓	✓	✓
Year × Quarter	✓	✓	✓	✓	✓	✓
Occupation (ISCO4)	✓	✓	✓	✓	✓	✓
MDV	1.296	1.296	1.330	1.330	8.093	8.093
N	111,696	111,696	111,696	111,696	66,522	66,522
R^2	0.748	0.748	0.806	0.806	0.739	0.739

Notes: This table shows the placebo check consisting in the Regression Discontinuity estimates for β in equation 6 for an incorrected imputed JVNO policy in the years 2014 and 2016. 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 2014-2016. *p < 0.10, **p < 0.05, ***p < 0.01.

Appendix D: Firm-level analysis, additional evidence

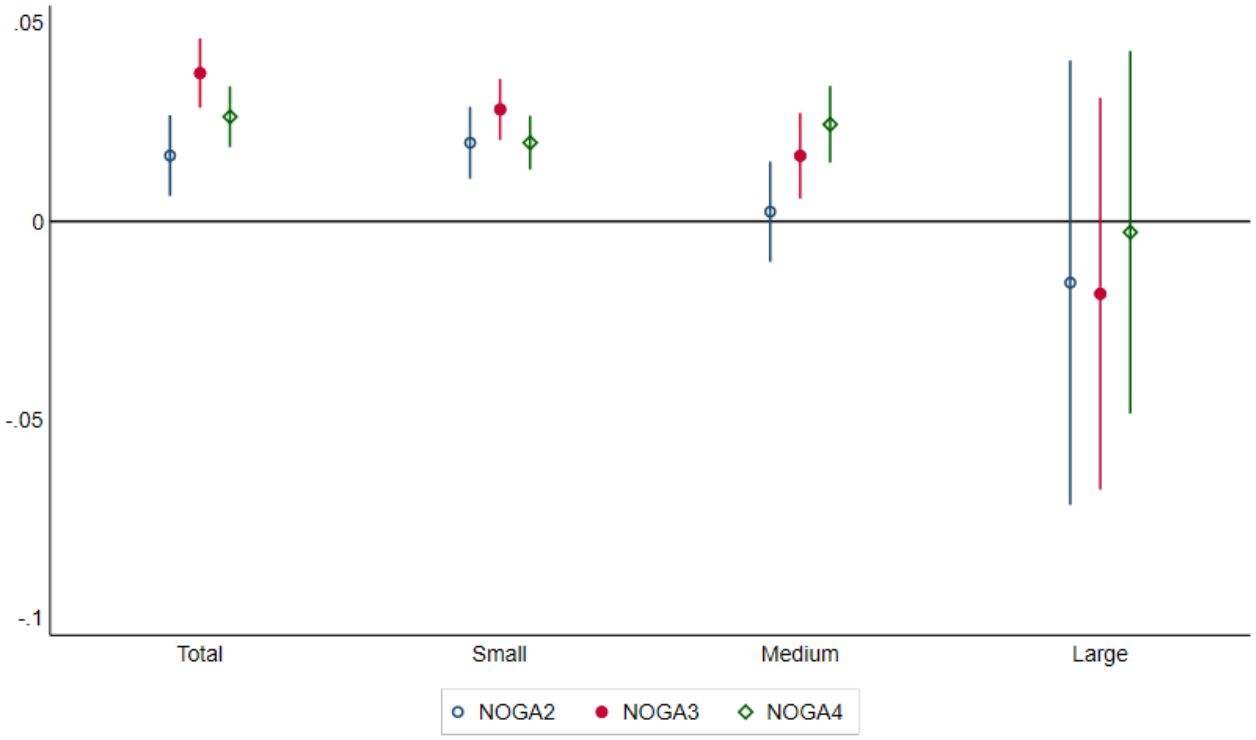


FIGURE D.13: ROBUSTNESS TO ALTERNATIVE INDUSTRY AGGREGATION LEVELS

Notes: The figure reports coefficient estimates and 95% confidence intervals for the effect of the JVNO exposure measure across alternative industry aggregation levels. While the main analysis uses NOGA 3-digit industries, this figure replicates the estimates using also NOGA 2-digit and NOGA 4-digit classifications. Estimates are shown for the full sample and by firm size (small, medium, and large). All specifications follow the baseline regression framework and include firm and year fixed effects, with standard errors clustered at the firm level. In addition, all regressions control for an unemployment exposure measure constructed analogously to the JVNO exposure, replacing the treatment indicator with the occupation-specific unemployment rate in the relevant JVNO year (i.e. the lagged unemployment rate).

Effects of Mandatory Job Postings on Labor Market Outcomes

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March, 2026

Online Appendix

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Online Appendix A: Conceptual framework

This section presents a simple equilibrium search-and-matching framework to guide the interpretation of the effects of the JVNO policy on firms' vacancy posting and labor demand. The setup follows the canonical job search and matching model with decreasing returns to labor and sticky wages, in the spirit of Michaillat (2012) and Algan et al. (2020). We further extend this framework to analyze the firms' decision to adopt a formal or informal hiring practice.

In this section we detail the conceptual framework to provide guidance on the interpretation on the effects of the JVNO policy on labor demand. Building on Michaillat (2012) and Algan et al. (2020), the model consists of a canonical job search model (Pissarides, 2000) with decreasing return to scale in the production function and sticky wages. We further extend the framework used in Algan et al. (2020) to analyze the firms' decision to adopt a formal or informal hiring practice.

The economy is in discrete-time and populated by a unit mass of workers, who are either employed n or unemployed u, with $u + n = 1$. Let v denote vacancies and define labor market tightness as $\theta = v/u$. Matches are formed through a constant-returns matching function, implying a job-finding probability $f(\theta) = \mu\theta^{1-\eta}$ and a vacancy-filling probability $q(\theta) = \mu\theta^{-\eta}$, where $\mu > 0$ is matching efficiency and $\eta \in (0, 1)$ is the unemployment elasticity of matching.

Jobs are destroyed with probability λ, and firms exit with probability δ. In steady state, employment is given by

$$n^B(\theta) = \frac{f(\theta)}{\lambda + \delta + f(\theta)}, \tag{OA.1}$$

which defines the Beveridge curve.[1]

Firms produce output using decreasing returns to labor. A firm with productivity a and employment n produces $y(a, n) = an^\alpha$, where $\alpha \in (0, 1)$.[2] Wages are sticky and scale with productivity according to $w(a) = \omega a^\gamma$, where $\omega > 0$ is the steady-state wage component and $\gamma \in [0, 1]$ captures wage flexibility. This formulation follows Algan et al. (2020) and allows wages to adjust only partially to productivity.

Finally, firms can recruit either informally or formally. Let $j \in \{I, F\}$ denote the recruiting channel. Informal posting involves a per-period cost k_I, while formal posting involves a lower marginal cost $k_F < k_I$ but requires a fixed adoption cost $F > 0$. The JVNO policy can then be interpreted as

[1] The Beveridge curve is conventionally represented in the unemployment-vacancy space. Here, we prefer to express it as employment as a function of market tightness for coherence with the rest of the model.

[2] Thus, we assume that the production technology exhibits decreasing return to scale, which can be justified by some factor (e.g. management, fixed capital) being fixed in the short run.

shutting down the informal channel and forcing firms either to switch to formal posting or not to post at all.

Firms and Market Labor Demand. Let $J_j(a)$ denote the value of a filled job and $V_j(a)$ the value of a vacancy under recruiting channel j. The Bellman equations are given by

$$J_j(a) = an_j(a,\theta)^{\alpha-1} - \omega a^{\gamma} + \beta(1-\lambda)(1-\delta)J_j(a), \tag{OA.2}$$

and

$$V_j(a) = -k_j + \beta(1-\delta)\left[q(\theta)J_j(a) + (1-q(\theta))V_j(a)\right]. \tag{OA.3}$$

By imposing the free entry condition, $V_j(a) = 0$, which implies $k_j/q(\theta) = \beta(1-\delta)J_j(a)$, and combining the two Bellman equations yields the following job-creation condition:

$$\alpha a n_j(a,\theta)^{\alpha-1} = \omega a^{\gamma} + \frac{k_j}{\beta(1-\delta)q(\theta)}\left[1-\beta(1-\lambda)(1-\delta)\right]. \tag{OA.4}$$

Thus, firms optimally equate the marginal product of labor to the wage and marginal cost of hiring, which is the wage plus the present discounted value of posting a vacancy. This condition determines the firm's labor demand for a given market tightness (θ) and firm productivity a, which we denote $D_j(a,\theta)$. Given the average productivity for firm hiring informally ($\bar{a}_I$), we can solve equation OA.4, and obtain the average labor demand for the informal hiring firms $D(0,\theta)$ as a function of θ. Absent of the formal hiring practice, the Beveridge curve (OA.1) and the labor demand (OA.4) jointly determine the level of employment $n(0)$ and the labor market tightness $\theta(1)$. Analogously, we can also derive the level of employment $n(1)$ and the labor market tightness $\theta(1)$ if all firms adopt a formal hiring practice.

Considering the case with an exogeneous τ share of firms that adopt a formal hiring practice and $(1-\tau)$ the informal hiring practice, we can aggregate the two labor demand functions and obtain the market level labor demand as

$$D(\tau,\theta) = \tau D(1,\theta) + (1-\tau)D(0,\theta). \tag{OA.5}$$

Equilibrium labor market tightness and employment are thus determined by the intersection of aggregate labor demand and the Beveridge curve.

Profits and posting decisions. To formalize whether the firms decide to adopt a formal or informal hiring practice, we now consider the firm's profits function. Retaking the decreasing return to scale production technology, justified by for example some factor being fixed in the short term, we further assume that firms in order to adopt a formal hiring practice have to invest in fixed non-recoverable set-up cost F, while the informal hiring practice does not require any set up costs. Each firm in order to keep their employment at the optimal level $n(a)^*$, they have to post v vacancies, such that the number of new hires $vq(\theta)$ is equal to the number of layoffs $\lambda n(a)^*$.

Therefore, the firms can choose between the following profit functions or the outside option to close the firm and obtaining zero profits.

$$\pi(n(a),\theta,Informal) = \sum_{t=0}^{\infty}(1-\delta)^t\beta^t\left(an(a)^\alpha - \omega a^\gamma n(a) - \frac{k_I}{q(\theta)}\lambda n(a)\right) \tag{OA.6}$$

$$\pi(n(a),\theta,Formal) = -F + \sum_{t=0}^{\infty}(1-\delta)^t\beta^t\left(an(a)^\alpha - \omega a^\gamma n(a) - \frac{k_F}{q(\theta)}\lambda n(a)\right) \tag{OA.7}$$

Consider a firm as atomistic, such that it takes market tightness and wages as given, we can re-arrange equation OA.4 to describe the optimal labor demand as a function of the firm productivity a, given θ:

$$n_j(a) = \left\{\frac{\omega a^{\gamma-1}}{\alpha} + \frac{k_j}{\alpha a}\frac{[1-\beta(1-\lambda)(1-\delta)]}{\beta(1-\delta)q(\theta)}\right\}^{\frac{1}{\alpha-1}} \tag{OA.8}$$

Now, it can be showed that for a value $a > \tilde{a}$ the firm will prefer to adopt the formal hiring practice rather than the informal hiring practice. Define $\tilde{\delta} := \beta(1-\delta)$ the probability for the firm to survive in the next period, then $\pi(n(a),\theta,Formal) \geqslant \pi(n(a),\theta,Informal)$ if

$$(k_I - k_F)\left(\frac{\lambda n(a)}{q(\theta)}\right) \geqslant (1-\beta\tilde{\delta})F \tag{OA.9}$$

Since $k_I > k_F$ by assumption, and $n'(a) > 0$, there exists a $\hat{a}$ such that for a given θ and any $a \geqslant \hat{a}$, $\pi_F \geqslant \pi_I$, and vice-versa if $a < \hat{a}$, $\pi_F < \pi_I$.[3]

[3]Here, we have carried out an additional simplification, we have conveniently ignored that $n(a)$ depends on the hiring practice $\{Informal, Formal\}$. However, this simplification is without loss of generality, as for any given a and θ, $k_I > k_F$, so $n(a,k_F) > n(a,k_I)$.

For the participation incentive, we need that $\pi(n(a), \theta, Informal) > 0$, or alternatively

$$\frac{an(a)^{\alpha} - \omega a^{\gamma} n(a) - \frac{\lambda n(a)}{q(\theta)} k_I}{1 - \tilde{\delta}} \geqslant 0$$

which we can simplify in

$$an(a)^{\alpha-1} - \omega a^{\gamma} - \frac{\lambda}{q(\theta)} k_I \geqslant 0 \tag{OA.10}$$

Therefore, looking at equation OA.8 we can notice that this condition is always satisfied independently of the value of a. Therefore, for each firm is at least preferred to post informally that do not enter the market at all.[4]

JVNO policy. Now, what happens if we suppress the possibility to post informally? Some firms will post formally and other will stop postings, depending on their productivity. Specifically, those firms with productivity greater than $\tilde{a}$ will post formally, and those below will stop postings. To derive $\tilde{a}$ we can find that a such that the firm is indifferent between posting formally or not posting at all, or in other words $\pi(n(\tilde{a}, \theta, Formal)) = 0$.

$$\frac{an(a)^{\alpha} - \omega a^{\gamma} n(a) - \frac{\lambda n(a)}{q(\theta)} k_F}{1 - \beta\tilde{\delta}} - F \geqslant 0 \tag{OA.11}$$

$$an(a)^{\alpha} - \omega a^{\gamma} n(a) - \frac{\lambda n(a)}{q(\theta)} k_F - F(1 - \beta\tilde{\delta}) \geqslant 0 \tag{OA.12}$$

Analogously as before, we can see that the left hand side is increasing in a, then there exists a reservation strategy, an optimal stopping rule, such for $a \geqslant \tilde{a}$, $\pi(n(a), \theta, Formal) \geqslant 0$. Moreover, we can also see that $\tilde{a} \leqslant \hat{a}$. Because $\hat{a}$ has to satisfy the following condition

$$an(a)^{\alpha} - \omega a^{\gamma} n(a) - \frac{\lambda n(a)}{q(\theta)} k_F - F(1 - \beta\tilde{\delta}) \geqslant an(a)^{\alpha} - \omega a^{\gamma} n(a) - \frac{\lambda n(a)}{q(\theta)} k_I \tag{OA.13}$$

and by the participation condition (OA.10) the right hand side is greater or equal than 0, therefore, if Equation OA.13 is satisfied also Equation OA.11 is satisfied, which implies that $\hat{a} \geqslant \tilde{a}$.

[4]This condition arises from the fact that the firms pay workers a share of their productivity. Therefore, even if the firms has a low productivity they found still profitable to hire a worker.

A.1 Simulation, Discussion, and Model Prediction

Building on the frameworks of Michaillat (2012) and Algan et al. (2020), we adopt the parameter values summarized in Table OA.A.1. Figure OA.A.1 illustrates firm posting decisions between formal and informal channels, along with the associated productivity thresholds, denoted by $\tilde{a}$ and $\hat{a}$. Figure OA.A.2 shows the initial market equilibrium and the changes induced by the introduction of the JVNO policy.

Initially, a proportion τ of firms posts vacancies formally, while the remaining share $(1-\tau)$ posts informally. Under these conditions, the market reaches an equilibrium represented by point T, which determines the prevailing level of labor market tightness. At this equilibrium, formally posting firms operate at point C, while informally posting firms correspond to point A.

Following the implementation of the JVNO policy, firms are no longer allowed to post vacancies informally. As a result, a share σ of previously informal firms transitions to formal posting, while the remaining fraction $(1-\sigma)$ exits the market. The post-policy economy is therefore characterized by a reduced mass of active firms, all of which post formally. These changes shift the aggregate job creation curve, denoted $D(\sigma, \theta)$ (purple dashed line), and lead to a new equilibrium at point M.

The policy generates three distinct effects. First, informal firms that switch to formal posting experience an increase in employment, captured by segment AE. Second, the increase in formal vacancy posting raises market tightness, which reduces vacancy-filling probabilities and generates a congestion effect. This effect lowers employment among firms that were already posting formally, illustrated by segment CE. Third, the exit of low-productivity firms reduces total job creation. The overall effect on employment therefore reflects the balance between switching, congestion, and exit.

Whether the policy increases or decreases aggregate employment is theoretically ambiguous. When the share σ of informal firms that transition to formal posting is sufficiently large, the expansion in labor demand from switching firms dominates, and both employment and market tightness increase (movement from T to M). However, when σ is low, the exit margin dominates and aggregate employment may decline despite the increase in formal recruiting efficiency.

Figure OA.A.3 explores these mechanisms quantitatively. Panel (a) varies the initial share of formal firms τ, holding $\sigma = 0.95$ fixed, and shows how the different components of the employment effect evolve with market composition. Panel (b) instead fixes $\tau = 0.55$ and varies the transition rate σ, isolating the role of policy effectiveness. The figures decompose the total effect into (i)

gains from switching (AC), (ii) congestion losses (CE), and (iii) net employment effects (AE), along with changes in labor market tightness (TM). Consistent with the theoretical discussion, higher values of σ mitigate the exit margin and amplify the positive effects of formalization, while congestion effects become stronger as more firms compete in the formal market.

Table OA.A.1: Parameters value for simulations

Parameter	**Description**	**Yearly**
μ	Matching efficiency	1.000
η	Matching elasticity (unemp.)	0.500
λ	Separation rate	0.108
δ	Firm exit/default rate	0.087
β	Discount factor	0.988
α	Returns to labor	0.666
a_I	Average Productivity (Informal)	0.600
a_F	Average Productivity (Formal)	1.250
k_I	Vacancy cost (Informal)	6.000
k_F	Vacancy cost (Formal)	3.000
ω	Steady-state Wage level	0.666
γ	Wage Flexibility	0.600
τ	Share of formal firms	0.550
σ	Share of informal firms shifting	0.950
F	Fixed cost (Formal)	0.666

Notes: Value of the parameters for Figures OA.A.1, OA.A.2, and OA.A.3.

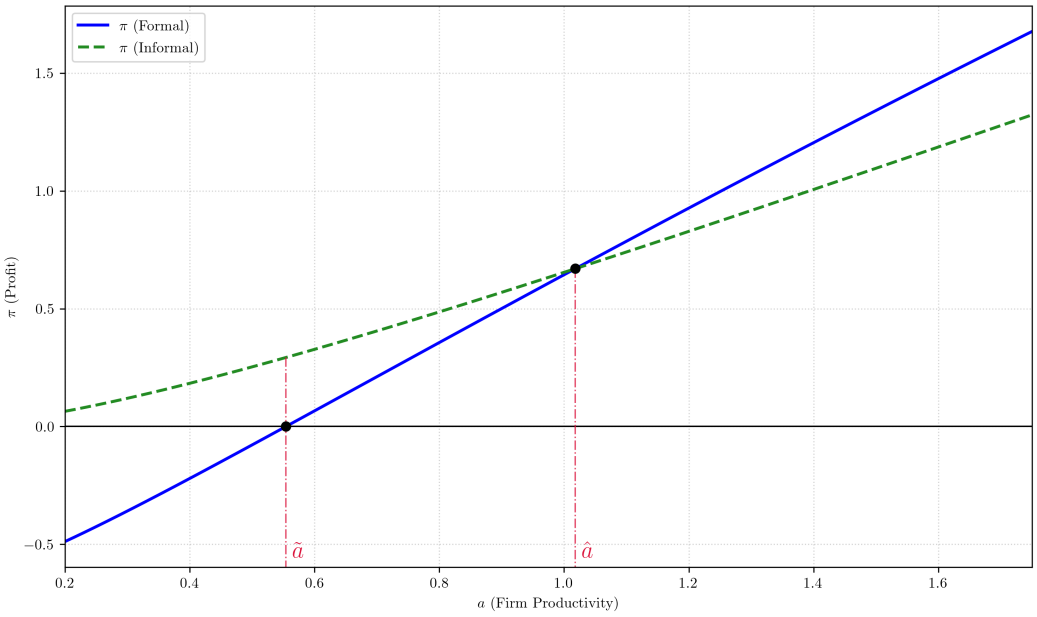
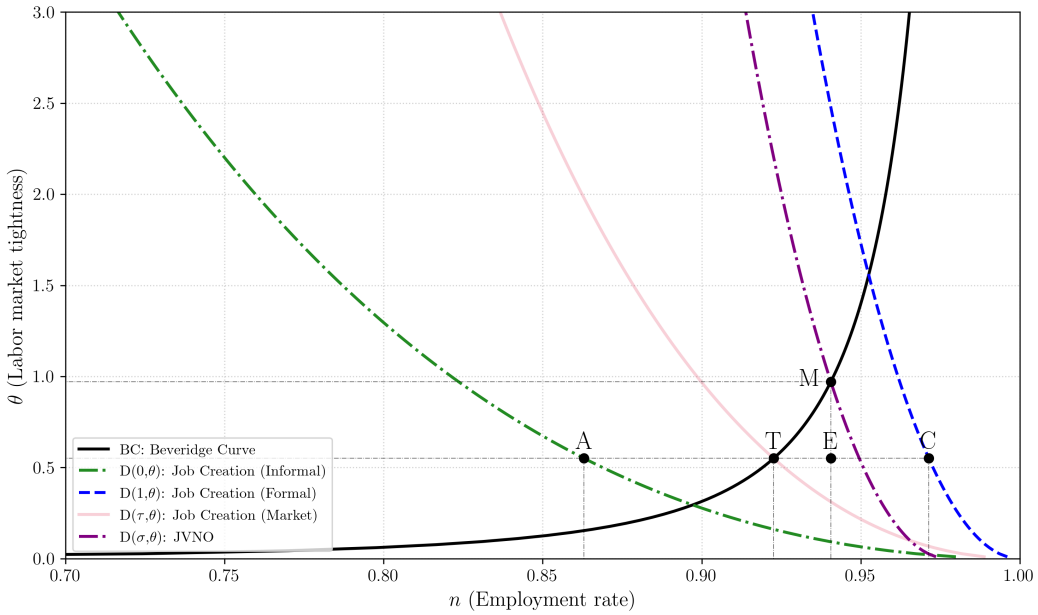
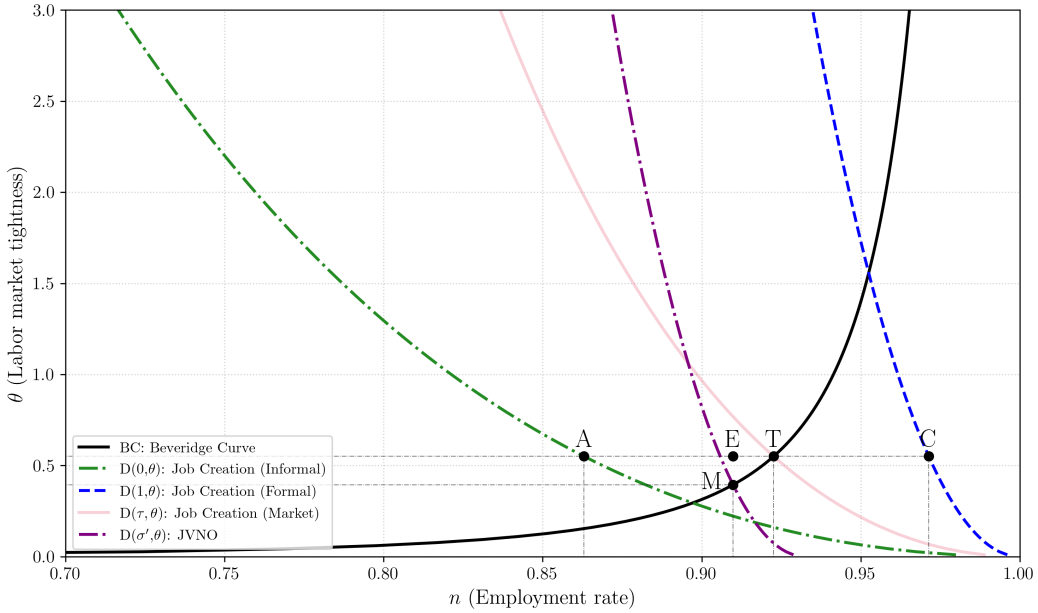


FIGURE OA.A.1: POSTING FORMAL OR INFORMAL: SIMULATION

Notes: This figure illustrates the profit functions for a firm choosing between formal (solid blue line) and informal (dashed green line) hiring strategies as a function of firm productivity. The red vertical lines indicate the two key thresholds: $\tilde{a}$ represents the productivity level above which a firm prefers posting formally over not hiring, while $\hat{a}$ marks the threshold above which formal hiring becomes more profitable than informal hiring. The parameters used for the simulation are detailed in Table OA.A.1.



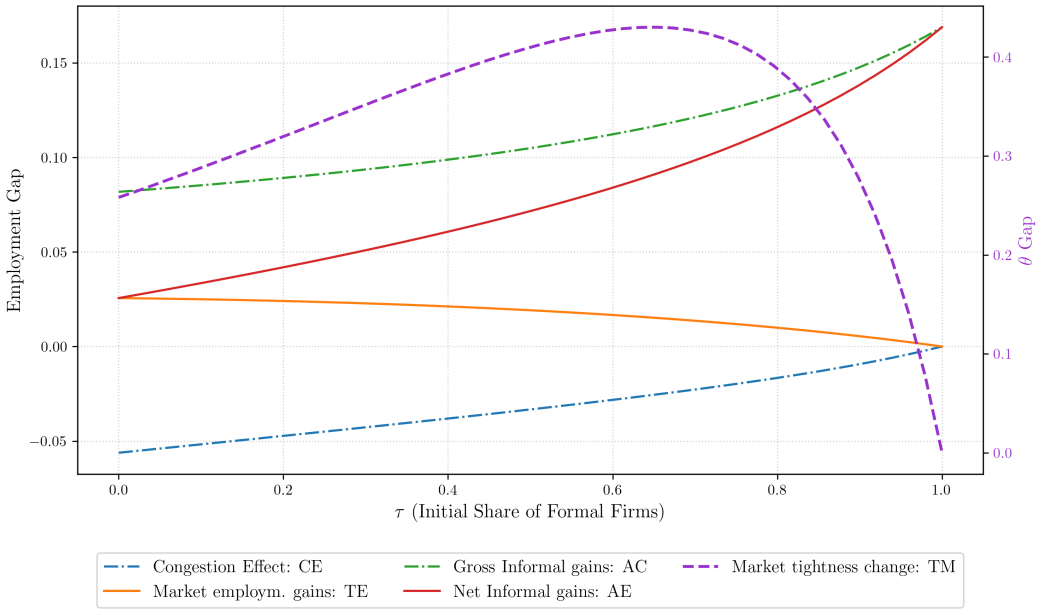
(A) Positive effect at the market level



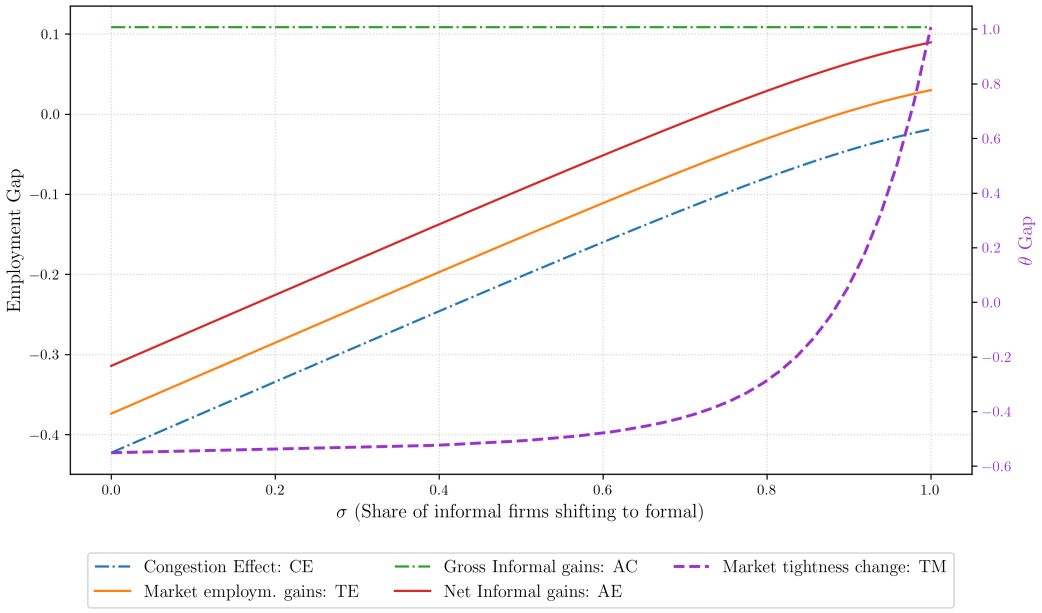
(B) Negative effect at the market level

FIGURE OA.A.2: JVNO EFFECT AT PARTIAL EQUILIBRIUM

Notes: This figure illustrates the model-implied changes in labor demand following the introduction of the JVNO policy, using the parameters specified in Table OA.A.1. The solid black line represents the Beveridge curve. The dashed green and dashed blue lines depict the labor demand functions for firms hiring informally and formally, respectively. The solid red line shows the aggregate labor demand prior to the policy, combining both types of firms. The dashed purple line represents the new aggregate labor demand after the implementation of the JVNO policy, which compels firms previously hiring informally to either exit the market or switch to formal vacancy posting. Panel B substitutes σ from 0.95



(A) Change in the share of formal posting firms



(B) changes in the share of informal posting firms switching to formal posting

Figure OA.A.3: JVNO effects: changes in τ and σ

Notes: This figure illustrates how the impact of the JVNO policy effect varies depending on the initial share of firms engaged in formal hiring prior to the policy (Subfigure A), and how it changes according to the share of informal firms shifting to formal hiring due to the policy (subfigure B). The value of the other parameters used in the simulation are reported in Table OA.A.1.

Online Appendix B: Construction of the Postings Sample

B.1 Job Posting Data

The job posting dataset is provided by x28 AG, a Swiss labor market analytics firm that continuously scrapes vacancy postings from a broad set of online sources, including firm websites, job portals, and recruitment platforms. The data span 2012–2024 and approximate the universe of publicly posted vacancies in Switzerland. x28 processes raw postings through a standardized pipeline that harmonizes formats, removes duplicates, and assigns detailed identifiers for occupation (ISCO-08, 4-digit), industry (NOGA), firm, and location.

To focus on employer-level labor demand and ensure data quality, we apply a set of conservative cleaning procedures. We restrict the sample to postings located in Switzerland, exclude vacancies advertised by recruiting agencies, and drop postings that remain active for more than one year. While recruiting agencies are an integral part of the labor market, their postings frequently duplicate those of hiring firms, potentially inflating vacancy counts.

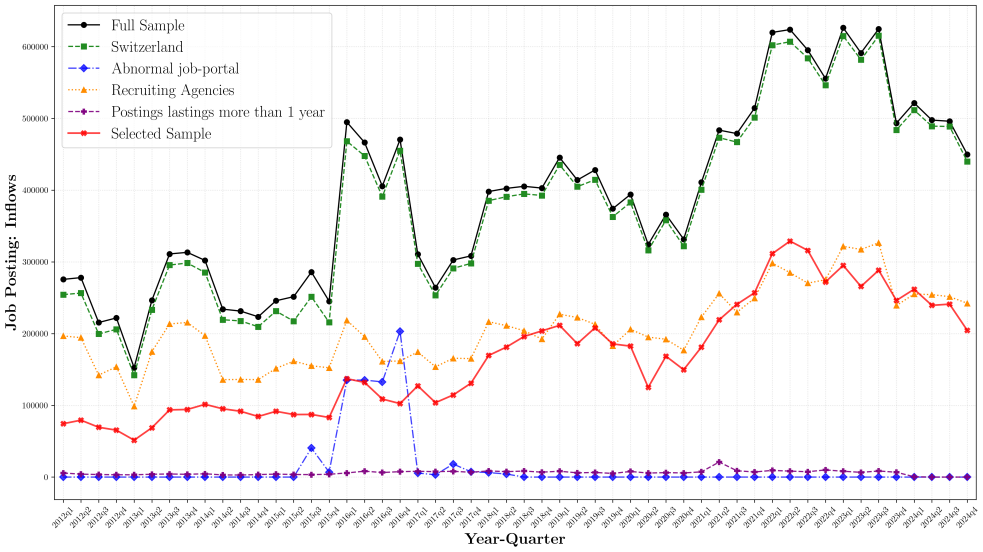
Figure OA.B.1 illustrates these cleaning steps and validates the resulting data against administrative vacancy statistics from JOBSTAT. For a comprehensive description of the dataset, classification procedures, and validation exercises, see Colella and Marcato (2024), who adopt the same cleaning strategy and document the high representativeness of x28 data.

B.2 JVNO Treated Occupations and Unemployment Rates

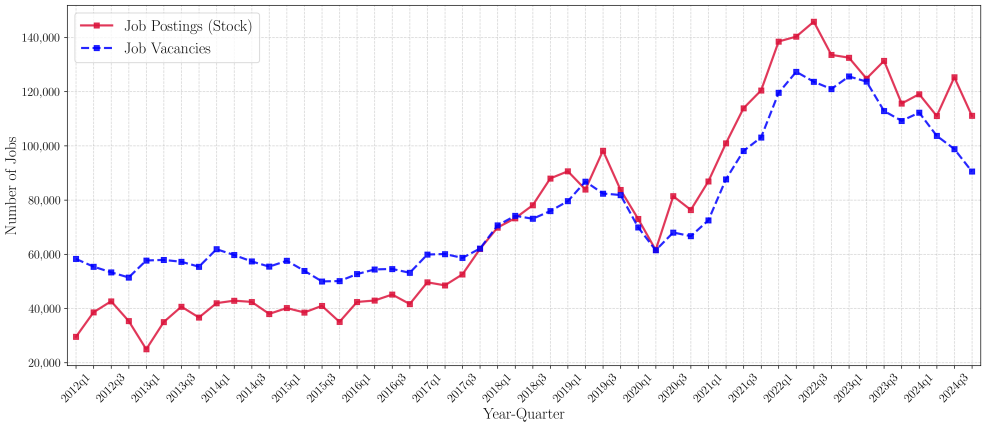
As described in Section 2, the JVNO policy was introduced in July 2018 and remains in force. Each year, the Swiss State Secretariat for Economic Affairs (SECO) computes occupation-specific unemployment rates using data from October 1 of year $t-2$ to September 30 of year $t-1$. Occupations with unemployment rates exceeding 5% are subject to JVNO requirements in year t.

The first implementation round (2018–2019) deviates from this framework along several dimensions. The reference period spans April 2017 to March 2018, the policy duration extends to 18 months (July 2018–December 2019), and the unemployment threshold is set at 8%. Most importantly, SECO relied on a different occupational classification system.

Specifically, the initial round uses the Swiss Standard Classification of Occupations 2000 (SSCO-2000), whereas from 2020 onward SECO adopts CH-ISCO-19, which aligns with ISCO-08 at the 4-digit level and adds a fifth digit specific to the Swiss labor market. This change enables a reliable



(a) Job posting cleaning



(b) Validation of job posting data

Figure OA.B.1: Job postings data: Cleaning and validation

Notes: Panel (a) illustrates the construction of the final job postings sample by reporting quarterly inflows of postings across different sources and filters. The selected sample excludes postings from abnormal job portals, recruiting agencies, and vacancies lasting more than one year, and restricts attention to Switzerland. Panel (b) validates the resulting series by comparing the stock of active postings with administrative vacancy data from JOBSTAT. To ensure comparability, both series are measured as the number of active postings at the end of each quarter. The two series closely track each other over time, supporting the representativeness of the cleaned dataset. Additional details are provided in Colella and Marcato (2024).

mapping to ISCO-08 from 2020 onward, but not for the first policy round.[5]

A further complication arises from the fact that JVNO treatment status is assigned at the 5-digit CH-ISCO level, with smaller occupations sometimes aggregated together.[6] To conduct our analysis at the 4-digit ISCO level, we aggregate treatment status and unemployment rates accordingly. Specifically, we compute the JVNO-relevant unemployment rate for each 4-digit ISCO code by summing the number of unemployed and employed workers across the corresponding 5-digit occupations. For the first policy round, which relied on SSCO-2000, we construct a crosswalk from SSCO to CH-ISCO-19 using a conversion table provided by SECO, based on the distribution of unemployed individuals across occupation codes.

This aggregation introduces measurement error. In particular, some 5-digit occupations may be treated even when the corresponding aggregated 4-digit unemployment rate falls below the threshold. Additional discrepancies arise from classification changes in the 2018–2019 period. Table OA.B.1 documents the extent of these mismatches across policy years, reporting the number of ISCO 4-digit occupations correctly matched to the official JVNO treatment list, as well as the number of job postings associated with correctly and incorrectly matched occupations.

To address this issue, our baseline analysis focuses on a corrected sample. We exclude the first JVNO round and restrict attention to occupations that are consistently classified between 2020 and 2024. Table OA.B.2 shows that observable characteristics are highly similar between the full and corrected samples. More generally, the distributions of key variables are broadly comparable across all sample definitions, suggesting that neither the exclusion of the first JVNO round nor the restriction to consistently classified occupations materially affects the composition of the data.

B.3 Robustness to Imperfect Construction of the JVNO Measure

To assess whether our results are sensitive to our sample restrictions and to the construction of the treatment variable, we examine a set of alternative specifications.

A first concern relates to the exclusion of the initial JVNO round. We therefore replicate the analysis including this period. A second concern arises from the aggregation of treatment status from 5-digit CH-ISCO occupations to the ISCO-4d level, which introduces measurement error in both the treatment indicator and the running variable. To address this issue, we consider two

[5] SSCO-2000 contains approximately 20,000 codes and is structured around economic activities rather than occupations. See Swiss Federal Statistical Office (2022b) and Swiss Federal Statistical Office (2022a) for details.

[6] The list of the most recent JVNO treated occupation announced, as well as some additional information, can be found at the following link: https://www.arbeit.swiss/secoalv/en/home/menue/unternehmen/stellenmeldepflicht/stellenmeldepflicht-ab-2025.html, Last Access: 25 April, 2025.

Table OA.B.1: Classification Accuracy of JVNO Treatment Status by Policy Year

	2018-2019		2020		2021		2022		2023		2024	
	#	%	#	%	#	%	#	%	#	%	#	%
Panel A: Occupations												
Correct	320	89.4%	350	97.8%	349	97.5%	350	97.8%	357	99.7%	356	99.4%
Misclassified	38	10.6%	8	2.2%	9	2.5%	8	2.2%	1	0.3%	2	0.6%
Panel B: Postings												
Correct	904,393	82.2%	563,332	98.7%	810,138	97.9%	1,101,939	97.8%	974,071	99.8%	836,634	99.4%
Misclassified	195,310	17.8%	7,687	1.3%	17,089	2.1%	24,420	2.2%	1,960	0.2%	5,305	0.6%

Notes: This table reports the number and share of correctly classified and misclassified 4-digit ISCO occupations (Panel A) and associated job postings (Panel B) by JVNO policy year. An occupation is correctly classified if its aggregated unemployment rate aligns with the official JVNO treatment status. Misclassification arises from aggregation from 5-digit CH-ISCO codes to the 4-digit ISCO level and from classification changes across policy rounds.

Table OA.B.2: Comparison of Summary Statistics Between Full and Corrected Samples

	Full sample 2020–2024	Restricted 2020–2024	Full sample 2018q3–2024	Restricted 2018q3–2024
Panel A: Market level				
Number of vacancies posted	23.070	23.514	21.766	20.737
	(99.240)	(101.686)	(93.726)	(84.687)
Number of posting firms	13.124	13.194	12.362	11.819
	(37.390)	(37.956)	(35.997)	(34.310)
HHI	4222.618	4254.611	4304.360	4361.023
	(3460.765)	(3475.039)	(3488.055)	(3493.709)
Unemployment rate	0.026	0.024	0.027	0.023
	(0.025)	(0.024)	(0.025)	(0.021)
Panel B: Vacancy level				
Vacancy duration (days)	39.906	40.204	40.104	39.761
	(50.353)	(50.664)	(50.889)	(50.075)
Number of skills	15.278	15.270	15.249	15.271
	(8.983)	(8.926)	(8.810)	(8.796)
Number of words	228.714	224.070	225.843	223.368
	(289.223)	(286.922)	(272.120)	(276.615)

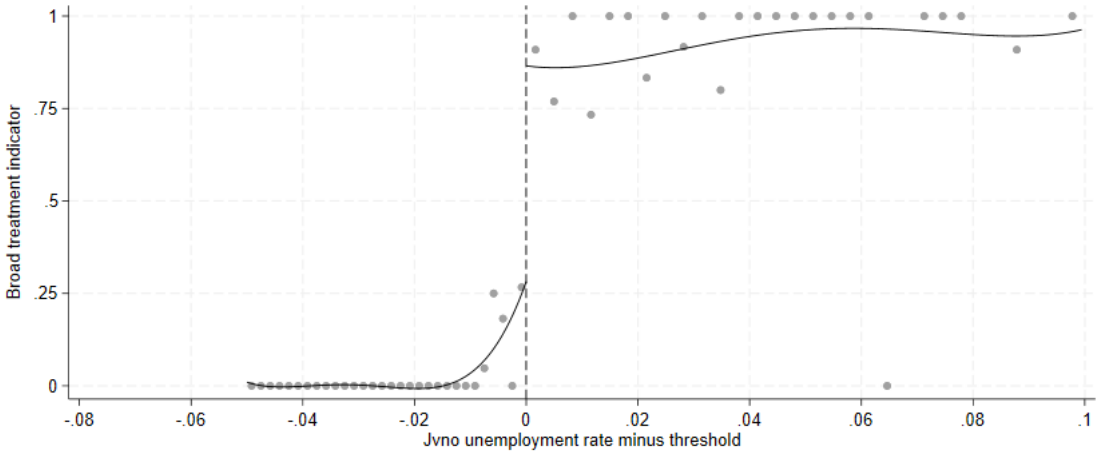
Notes: This table compares summary statistics between the full sample of job postings and the corrected sample excluding occupations with inconsistent JVNO treatment classification. Panel A reports market-level variables (occupation × canton × quarter), while Panel B reports vacancy-level characteristics. Means and standard deviations are shown. The similarity across samples suggests that misclassification is not systematically related to observable labor market outcomes.

alternative treatment definitions.

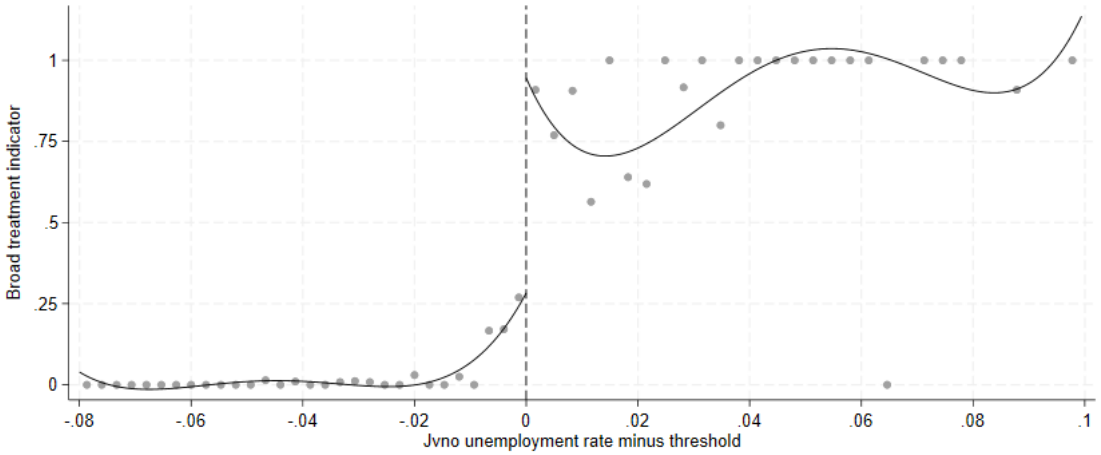
First, we implement a *reduced-form* specification, in which occupations are classified as treated whenever their aggregated ISCO-4d unemployment rate exceeds the 5% threshold, irrespective of the underlying 5-digit treatment assignment. Second, we estimate a *fuzzy regression discontinuity design*, where an ISCO-4d occupation is considered treated if at least one of its underlying CH-ISCO-5d occupations is officially subject to JVNO, and instrument this treatment with an indicator for whether the aggregated unemployment rate exceeds the threshold.

Figure OA.B.2 reports the first-stage relationship for the fuzzy design, both excluding and including the first JVNO round. In both cases, we observe a clear discontinuity in the probability of treatment at the threshold, supporting the relevance of the instrument.

Figure OA.B.3 summarizes the estimated effects on the inverse hyperbolic sine of the number of job postings and posting firms across specifications. We report estimates for the baseline specification, as well as for samples that include the first JVNO round, and for both reduced-form and fuzzy treatment definitions. Across all specifications, the estimates are quantitatively similar and statistically consistent, indicating that our findings are not driven by sample selection or by the specific construction of the treatment variable.



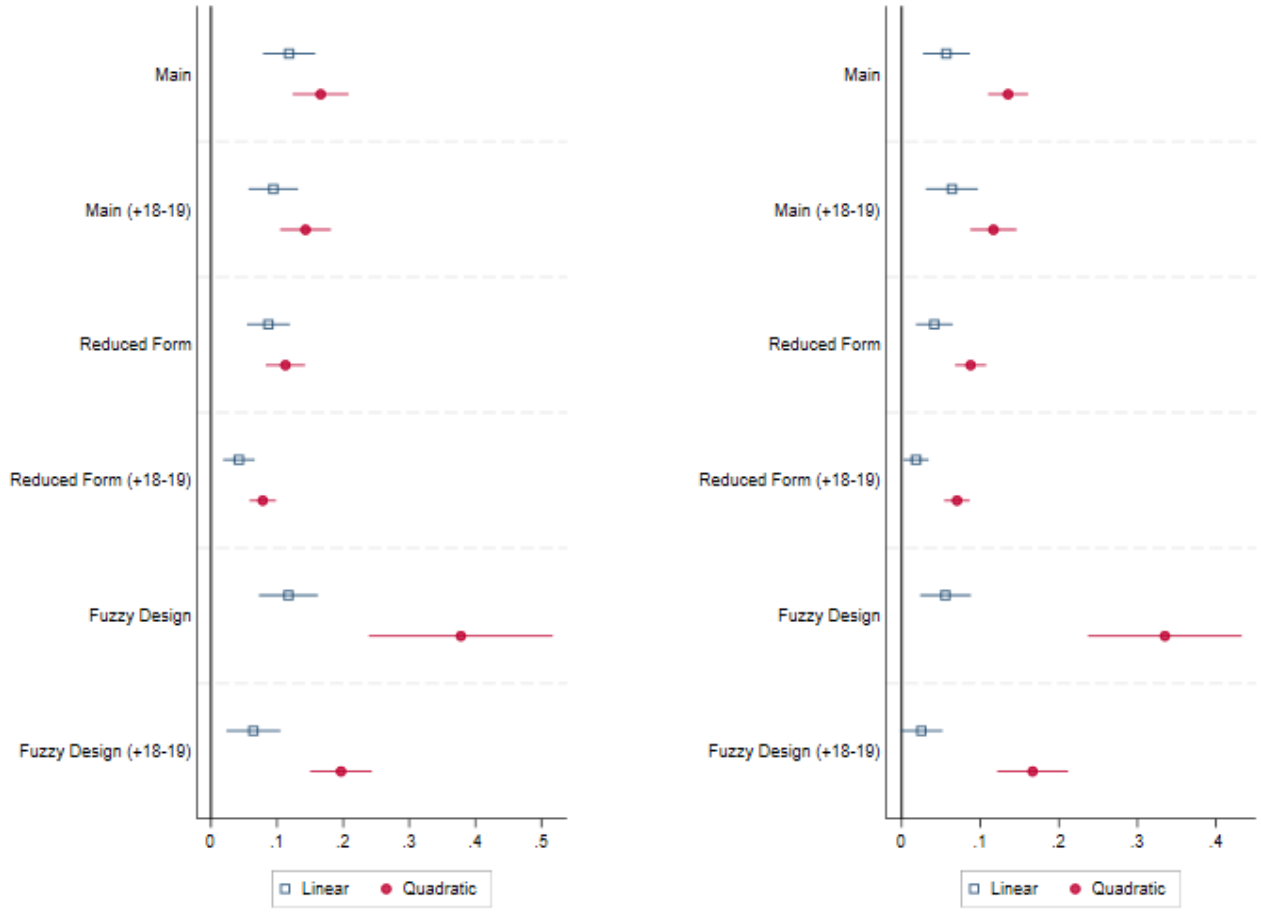
(A) Sample: 2020–2024



(B) Sample: 2018q3–2024

Figure OA.B.2: Fuzzy RD: First stage

Notes: The figure presents the first-stage relationship in the fuzzy regression discontinuity design. The outcome is an indicator equal to one if at least one underlying 5-digit CH-ISCO occupation is treated. The running variable is the JVNO-relevant unemployment rate (aggregated at the ISCO-4d level) minus the treatment threshold. Dots represent bin averages, and solid lines are local polynomial fits. Panel (a) uses the main sample (2020–2024), while Panel (b) additionally includes the first JVNO round (2018q3–2019q4).



(A) Job postings (B) Posting firms

FIGURE OA.B.3: ROBUSTNESS TO ALTERNATIVE JVNO TREATMENT DEFINITIONS

Notes: The figure reports RD estimates of the effect of the JVNO policy under alternative treatment definitions. "Main" uses the preferred specification, restricting to occupations that are always correctly classified. "Reduced form" assigns treatment based on whether the aggregated unemployment rate exceeds the threshold. "Fuzzy design" defines treatment at the ISCO-4d level if at least one underlying CH-ISCO-5d occupation is treated. Specifications labeled "(+18–19)" additionally include the first JVNO policy round. Blue markers correspond to linear specifications and red markers to quadratic specifications. All regressions include canton, year-quarter, and occupation fixed effects, and standard errors are clustered at the firm level.

Online Appendix C: Construction of the Matched Sample

This section describes the procedure implemented to associate each individual identifier (AVS ID) in the Social Security data (AVS) to a Firm ID (UID) present in the Firm Registry (STATENT). To create the association we use three databases containing both identifiers for subgroups of workers: the Unemployment Registry (AVAM), the Swiss Earnings Structure Survey (ESS), and the Migration Registry (ZEMIS). We follow the following steps.

1. Select all firms in STATENT.
2. Load AVAM data containing, the ID of the last employer, the ID of the new employer, the registration date and the data in with the new job starts.
3. Divide the AVAM dataset into two different datasets: AVAM Entering Unemployment and AVAM Exiting Unemployment.
4. Load employment spells, by year, retrieved from the social security database (AVS). Here the proxy for the firm is constructed using the pair `n_cassie` and `naffilie`. For persons with multiple contemporaneous employments we select the longest employment spell.
5. Load the selected sample of people moving out of unemployment and collapse to a single month per exit date–UID pairing, considering only the available maximum month. We keep only a unique combination of AVS ID and date of new job beginning, preferring the one associated to a UID with a longer spell. We add an extra month to the date of new job beginning, in case employment starts the month after the last recording in the AVS data. We prefer exact match if available and drop unnecessary rows created when expanding the datasets to allow for greater tolerance. We do the same for the people moving into unemployment using the information on the previous spell.
6. Match the ESS Survey Data with selected UID from Step 1. Since ESS data are recorded each year in October, select only the AVS ID, the corresponding UDI, and the observation date that include October. Also here we keep a unique combination of AVS ID following the same reasoning above. Note that ESS data are available only at biannual frequency.
7. Match the ZEMIS Data with selected UID from Step 1. The variable `stich_jm` is used to construct the observation date (which refers to December of the year of interest). Also here we keep only a unique combination of AVS ID and date of observation.
8. Combine all sources to validate the employer–UID mapping by concatenating the datasets obtained previously by merging the UID sources with AVS spells. For each year, keep only

AVS ID, EMPLOYER ID (which is the unique combination of `n_cassie` and `naffilie`), UID, total employment in STATENT. For each AVS ID - EMPLOYER ID - UID combination we: (i) count the number of observations, the number of observations per employer, the total number of EMPLOYER ID and UID, the number of observations per EMPLOYER ID and UID, and the share of each UID with the same EMPLOYER ID.

9. We apply the following filtering logic. We evaluate the share of total observations for each employer that are associated with a given UID number, and we remove combinations that fall below a certain threshold. These thresholds are defined based on the total number of employees for the UID, under the assumption that larger firms are more likely to have multiple UID, while smaller firms should exhibit higher UID consistency. I particular, for small employers [1,20], retain only combinations where at least 95% of the employer's observations are associated with the same UID. For medium employer [20,100] the required minimum share is 90%. For large employers [100,1000], the required minimum share is 85%. For very large firms [> 1000], the required minimum share is 80%. At the end of this procedure we have only one corresponding UID to each EMPLOYER ID in each year. In a few cases the UID associated to an EMPLOYER ID can change by year. To increase the quality of matches only unique correspondences between UID and EMPLOYER ID is considered.

Table OA.C.1 shows descriptive statistics between the main sample used in the paper (STATENT) and the final sample constructed using this procedure (Matched Sample STATENT-AVS).

TABLE OA.C.1: BALANCING AVS-MATCHED OF FIRM CHARACTERISTICS, 2020-2023

	AVS-matched		Employment sample	
	Freq (1)	Percent (2)	Freq (3)	Percent (4)
Total	315,000	100	1,380,351	100
Average UIDs by year	78,750	100	345,088	100
Panel A: Firm size				
Average employees	13.8	100	7.6	100
Male average employees	8	58.25	4.3	56.43
Female average employees	5.8	41.75	3.3	43.57
Panel B: Major region				
Lake Geneva Region	64,915	20.61	254,150	18.41
Espace Mittelland	60,188	19.11	286,066	20.72
North-Western Switzerland	36,445	11.57	156,811	11.36
Zürich	54,454	17.29	222,679	16.13
Eastern Switzerland	43,208	13.72	206,803	14.98
Central Switzerland	34,252	10.87	177,025	12.82
Ticino	21,538	6.84	76,817	5.57
Panel C: Industry				
A. Agriculture, forestry and fishing	3,463	1.10	158,335	11.47
B. Mining and quarrying	386	0.12	866	0.06
C. Manufacturing	35,524	11.28	102,463	7.42
D. Electricity, gas, ...	608	0.19	2,465	0.18
E. Water supply....	1,619	0.51	5,014	0.36
F. Construction	39,374	12.50	137,707	9.98
G. Wholesale and retail trade...	53,168	16.88	188,873	13.68
H. Transportation and storage	7,229	2.29	28,405	2.06
I. Accommodation and food service activities	28,765	9.13	91,267	6.61
J. Information and communication	14,161	4.50	52,264	3.79
K. Financial and insurance activities	8,513	2.70	39,895	2.89
L. Real estate activities	8,949	2.84	45,500	3.30
M. Professional, scientific and technical activities	43,835	13.92	191,547	13.88
N. Administrative and support service activities	15,369	4.88	60,138	4.36
O. Public administration and defence...	1,890	0.60	9,129	0.66
P. Education	4,271	1.36	27,722	2.01
Q. Human health and social work activities	23,639	7.50	122,474	8.87
R. Arts, entertainment and recreation	5,678	1.80	33,100	2.40
S. Other service activities	18,559	5.89	83,187	6.03

Notes: The table compares characteristics of firms (UID) that can be matched to AVS with the sample of firms used in the employment analysis. Observations are at UID-year level. Columns (1)–(2) report statistics for the AVS-matched sample, which includes only matched UIDs with more than one employee, a difference of fewer than 500 employees compared to STATENT, and an absolute percentage difference below 100%. Columns (3)–(4) report frequencies for all the UIDs used in the employment analysis. Columns (5)–(6) report frequencies for the subgroup of UIDs used in the employment analysis with more than one employee. Period: 2020–2023.

Online Appendix D: Details of the Exposure Measure

While the regression discontinuity analysis identifies the effects of the JVNO policy by comparing occupations around the treatment threshold, it delivers estimates that are inherently relative across occupations. In particular, these effects may reflect a reallocation of labor demand across occupations rather than changes in overall employment. To complement this approach, we construct an industry-level exposure measure that captures the intensity with which firms are affected by the policy based on their pre-policy occupational composition. This allows us to assess whether the JVNO policy translates into broader changes in employment outcomes beyond shifts across occupations.

A key challenge in implementing this approach is the lack of detailed firm-level information on the occupational composition of employment prior to the policy. To address this limitation, we approximate firm-level exposure using industry-level variation. Specifically, we combine firms' industry classification with the pre-policy occupational structure of each industry to obtain a measure of exposure that varies across industries and over time.

The resulting measure follows a shift-share structure (Borusyak et al., 2025), where the shares are given by the pre-policy distribution of occupations within industries and the shifts correspond to the JVNO treatment status of occupations over time. To account for the fact that treatment assignment is not fully random, we also control for an analogous shift-share measure constructed using occupation-level unemployment rates.

To construct the industry-level exposure measure, we use data from the Structural Survey (SE) to estimate the occupational composition of each industry in the pre-policy period (2012–2015). These shares are fixed over time and therefore unaffected by the introduction of the JVNO policy.

We define the exposure of industry i in year t as the weighted share of treated occupations, where the weights correspond to the pre-policy employment shares:

$$NOGA_d Expo_{it} = \sum_o share_{io(2012\text{–}2015)} \times Treatment_{ot} \tag{OA.14}$$

$$share_{io(2012\text{–}2015)} = \frac{Employment_{io(2012\text{–}2015)}}{\sum_o Employment_{io(2012\text{–}2015)}}$$

where d denotes the level of aggregation in the NOGA classification, i indexes industries, and o denotes occupations defined at the 4-digit ISCO level. The variable *Employment* refers to the

total number of workers employed in industry i and occupation o during the pre-policy period.

We construct the exposure measure at different levels of industry aggregation (NOGA 2-digit, 3-digit, and 4-digit). In the empirical analysis, we focus on the NOGA 3-digit level, which provides a balance between granularity and statistical precision.

Figure **??** illustrates the distribution of the exposure measure across industries and years. The distribution is right-skewed, with most industries exhibiting relatively low exposure, while a subset of industries is substantially more affected by the policy. Table OA.D.1 reports summary statistics, showing that average exposure is around 10 percent, with a median of approximately 7 percent and a long right tail reaching values above 60 percent.

Using the same occupational shares, we construct an industry-level JVNO-related unemployment rate as:

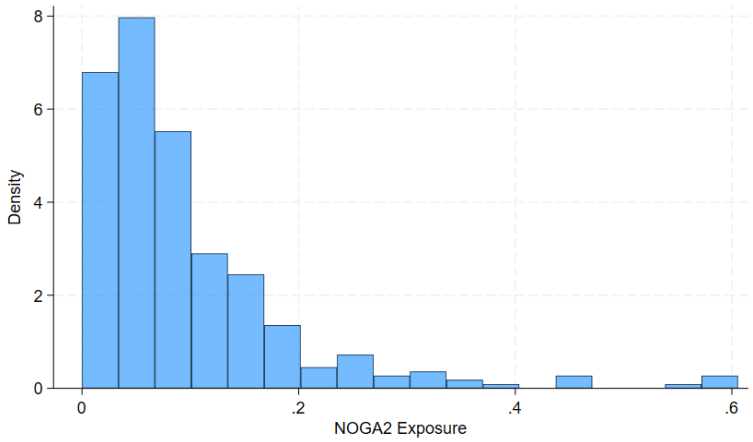
$$NOGA_d u_{it} = \sum_o share_{io(2012\text{–}2015)} \times u_{ot} \tag{OA.15}$$

where u_{ot} denotes the occupation-level unemployment rate in year t, which determines JVNO treatment assignment. This variable is included as a control to account for differential exposure to underlying labor market conditions across industries.

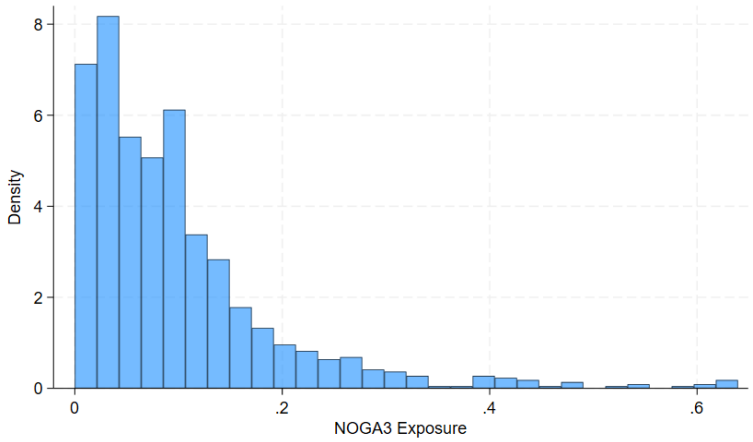
Table OA.D.1: Industry: Exposure Measure Distributions

	N	Mean	SD	Min	P25	Median	P75	Max
NOGA2	328	.0955586	.095167	0	.0360173	.0679812	.1191513	.6056872
NOGA3	1027	.0983194	.0974833	0	.0332787	.0746207	.1264228	.6394207
NOGA4	2318	.1002937	.1055061	0	.0288468	.0702387	.1335783	.7254643

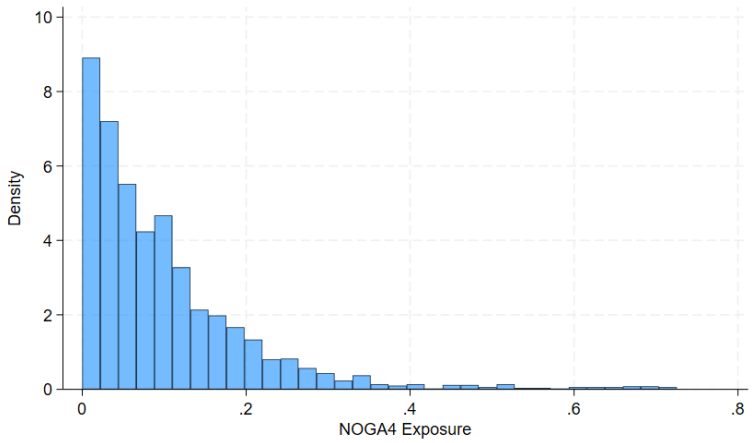
Notes: This table reports summary statistics for the industry-level exposure measure defined in equation OA.14. Each observation corresponds to an industry-year pair over the period 2020–2023.



(A) NOGA 2



(B) NOGA 3



(C) NOGA 4

FIGURE OA.D.1: INDUSTRY: EXPOSURE MEASURE DISTRIBUTIONS

Notes: The figure illustrates the distribution of exposure to the JVNO policy at the industry level, following equation OA.14. Each observation corresponds to a year–industry (NOGA) pair over the period 2020–2023.

Online Appendix E: Firm-level Job Posting effects

We complement the main analysis by examining how exposure to the JVNO policy affects firms' vacancy posting behavior. Using the industry-level exposure measure described in the Appendix D, we assign to each firm the exposure corresponding to its industry and estimate its effect on the number of job postings at the firm-year level.

Specifically, we regress the inverse hyperbolic sine (IHS) transformation of the number of job postings made by each firm in a given year on the industry exposure measure. All specifications include firm fixed effects, so identification relies on within-firm variation in exposure over time. The inclusion of firm fixed effects ensures that these results are not driven by differences in firm size or baseline posting intensity across firms.

Table OA.E.1 reports the results. We find a positive and statistically significant effect of exposure on firms' vacancy posting activity. Firms operating in industries that are more exposed to the JVNO policy increase their number of job postings, consistent with the evidence from the occupation-level analysis.

To assess the robustness of the results to the treatment of zeros and functional form assumptions, we consider alternative outcome specifications. In addition to the IHS transformation, we estimate models using a Poisson pseudo-maximum likelihood (PPML) estimator, a dummy indicator for whether the firm posts at least one vacancy in a given year, and a log specification restricted to firm-years with positive postings.

Across these specifications, the results are qualitatively similar, showing a consistently positive relationship between exposure to the JVNO policy and firm-level vacancy posting. However, the magnitude of the effects is stronger when using specifications that capture variation in the number of postings (IHS and PPML) than when focusing on the extensive margin (dummy specification). This pattern suggests that the effect of the policy operates strongly through the intensive margin, i.e., by increasing the number of vacancies posted by firms that are already active. This evidence is consistent with the main analysis, where the increase in labor demand is driven both by entry and by higher posting intensity, but the latter plays a stronger role.

Table OA.E.1: Comparison of Summary Statistics Between Full and Corrected Samples

	(1) IHS	(2) PPML	(3) Dummy	(4) Log	(5) IHS × 100
Exposure	0.101***	0.226**	0.044***	0.238***	0.303***
	(0.005)	(0.106)	(0.003)	(0.028)	(0.019)
NOGA3 un.rate	✓	✓	✓	✓	✓
Employer FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
NOGA3 FE	✓	✓	✓	✓	✓
MDV	0.276	9.178	0.136	1.400	1.256
N	1,780,408	441,455	1,780,408	209,354	1,780,408
R^2	0.826	0.907	0.674	0.820	0.740

Notes: This table reports estimates of the effect of the industry exposure measure on the number of job postings at the firm level. The unit of observation is a firm-year, and the dependent variable is the number of vacancies posted by the firm. Columns (1)–(5) report results using alternative functional forms of the outcome variable: inverse hyperbolic sine (IHS), Poisson pseudo-maximum likelihood (PPML), a binary indicator for positive postings, the logarithm (excluding zeros), and a rescaled IHS transformation (IHS × 100). All specifications include employer, year, and industry (NOGA 3-digit) fixed effects and control for the industry-level unemployment exposure measure. Job Posting sample: 2020-2024. Standard errors are clustered at the firm level. *p < 0.10, **p < 0.05, ***p < 0.01.

Online Appendix F: Job Postings Characteristics

While the evidence presented so far shows that the JVNO policy increased the number of job postings and posting firms, an open question is whether it also affected the nature of labor demand. In particular, the expansion in vacancies may have altered job characteristics, either through congestion effects (e.g., longer vacancy durations) or through adjustments in firms' hiring requirements and job amenities.

To investigate these mechanisms, we analyze job postings at the vacancy level, comparing observations just below and above the policy threshold. This approach allows us to include employer fixed effects and compare postings from the same firm across treated and untreated occupations, thereby isolating within-firm adjustments in job characteristics from compositional changes driven by firm entry.

Job postings provide a rich source of information on employer behavior. Beyond their primary role of attracting applicants, they contain detailed information on skill requirements, working conditions, and job amenities. A growing literature exploits these data to study labor demand and job characteristics, including skill requirements (Deming and Kahn, 2018; Deming and Noray, 2020; Atalay et al., 2020; Acemoglu et al., 2022; Atalay et al., 2024), flexible work arrangements (Adams et al., 2023), remote work (Hansen et al., 2023; Bloom et al., 2023), training provision (Adams et al., 2022), and broader workplace attributes (Audoly et al., 2024).

Switzerland's multilingual environment implies that job postings are written in several languages. Figure OA.F.1 reports the distribution of postings by language in the selected sample. Approximately 80% of postings are written in German, reflecting both the dominance of the German-speaking region and the location of the data provider.[7] French and English account for a smaller share, while Italian and other languages are negligible. A small fraction of postings is classified as "unknown", typically corresponding to multilingual job descriptions. Figure OA.F.2 shows that the language composition remains stable over time.

The presence of multiple languages poses challenges for text analysis. To address this, we conduct the analysis separately for the main languages and apply a harmonized preprocessing procedure. Specifically, we convert text to lowercase and remove extra whitespace, punctuation, and special characters, while avoiding more aggressive transformations such as stop-word removal or lemmatization, which may distort cross-language comparability.

[7] Some firm websites dynamically adapt language based on IP location, which may further contribute to the predominance of German-language postings in the data.

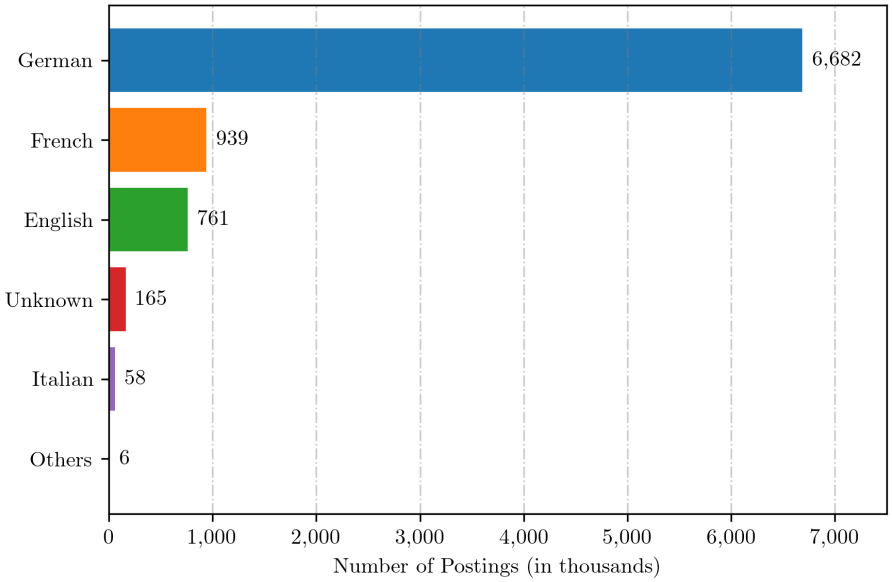


FIGURE OA.F.1: JOB POSTINGS TEXT LANGUAGE: NUMBER

The figure displays the number of job postings written in German, French, English, Italian, and Other languages. The "Unknown" category includes job postings where the language is unclear, primarily due to multilingual job descriptions. The "Others" category encompasses all remaining languages. Data source: Job Posting Data, selected sample. Period: 2012–2024.

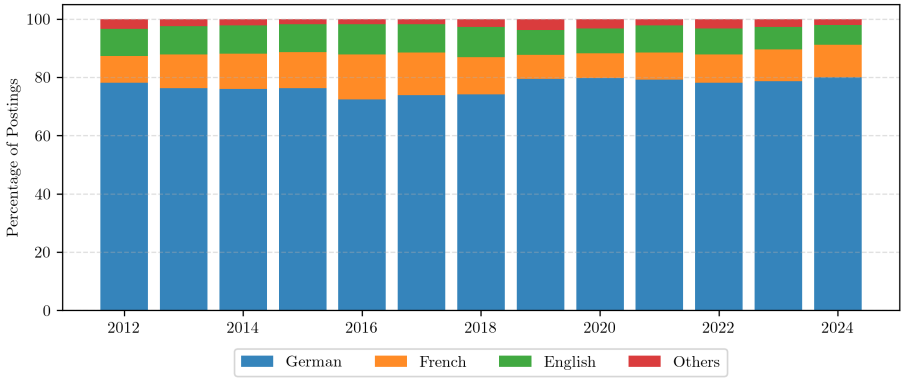


FIGURE OA.F.2: JOB POSTINGS TEXT LANGUAGE: PERCENTAGE OVER TIME

The figure illustrates the percentage of job postings written in German, French, English, and Others languages. The "Others" category includes all remaining languages, including postings where the language is unknown. Data source: Job Posting Data, selected sample. Period: 2012–2024.

We characterize job postings along two dimensions. First, we consider job-level attributes such as vacancy duration, contract type, work arrangements, and skill requirements. Second, we analyze textual features of job descriptions, including their length and readability. Textual complexity is measured using the number of words, sentences, syllables, and complex words (defined as words with at least three syllables), as well as standard readability indices (Kincaid, 1975). In particular, we compute the Flesch Reading Ease Score (FREST), the Automated Readability Index (ARI), and the Gunning Fog Index (GFI). While these measures were originally developed for English, they remain informative for assessing relative changes in readability across postings, although their absolute interpretation should be treated with caution in a multilingual setting. Specifically, we use the following formula.

1. The Flesch Reading Ease Score Test (FREST) is computed as:

$$FREST = 206.835 - 1.015\left(\frac{\text{total words}}{\text{total sentences}}\right) - 84.6\left(\frac{\text{total syllables}}{\text{total words}}\right).$$

   For German text, following Amstad (1978), we modify the formula to:

$$FREST_{\text{German}} = 180 - 1.015\left(\frac{\text{total words}}{\text{total sentences}}\right) - 58.5\left(\frac{\text{total syllables}}{\text{total words}}\right).$$

2. The Automated Readability Index (ARI) is given by:

$$ARI = 4.71\left(\frac{\text{total characters}}{\text{total words}}\right) + 0.5\left(\frac{\text{total words}}{\text{total sentences}}\right) - 21.43.$$

3. The Gunning Fog Index (GFI) is calculated as:

$$GFI = 0.4\left[\left(\frac{\text{total words}}{\text{total sentences}}\right) + 100\left(\frac{\text{total complex words}}{\text{total words}}\right)\right].$$

Figure OA.F.3 summarizes the estimated effects of the JVNO policy on job posting characteristics. Overall, we find limited evidence that the policy substantially altered the nature of job postings. Vacancy duration does not increase following the introduction of the policy; if anything, estimates suggest a modest decline. This result should be interpreted with caution, as JVNO postings are not publicly visible during the first five days, implying that observed durations may understate the effective exposure of vacancies to job seekers.

We also find small adjustments in job amenities and contract characteristics. The probability of offering remote work increases slightly, while the share of fixed-term contracts declines and the

average work quota decreases. These effects are economically modest and, in some cases, only weakly statistically significant.

Turning to skill requirements, postings in treated occupations exhibit a slight increase in the number of skills and languages requested. However, we find no meaningful changes in the composition of tasks, as measured by the share of skills that are remotable or automatable.

Finally, job descriptions become somewhat longer and easier to read, with increases in the number of words and sentences and improvements in standard readability metrics. These patterns suggest that firms may provide slightly more detailed and accessible job descriptions following the introduction of the policy.

Across all outcomes, the estimates are consistent across specifications using linear and quadratic fits of the running variable and when controlling for employer fixed effects. Taken together, these findings indicate that the JVNO policy primarily affected the quantity of labor demand, with only limited and relatively modest adjustments in the characteristics of job postings.

Figure OA.F.3: RD JVNO effects of Job Postings characteristics



The figure presents the coefficients and 95% robust confidence intervals clustered at the Canton level from Regression Discontinuity (RD) estimates of job postings characteristics. Panel (A) reports results for the log. duration in days, a dummy for the possibility of homeoffice, the log. number of skill demanded, the log. number of languages demanded, the share of remotable skills, the share of automatable skills. Panel (B) presents the log. the words in the job posting text, the log. number of sentences, the log. average number of syllables per word, the log. of the Automated Readability Index score (ARI score), the log. of the Flesch Reading Ease Score (Flesch Score), and the log. of the Gunning-Fog Index (Fog Index). The formula for these measures is described in Appendix **??**. Each observation is a job posting. All specifications include both a linear and a quadratic polynomial of the running variables, as well as Canton, year-quarter, and occupation fixed effects. Panel B Job Text metrics variables include also language fixed effects and it is limited to German, French, and English job postings. Sample: Job Postings dataset, period 2020–2024.