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The Effects of a Job Creation Scheme:
Evidence from Regional Variation in Program Capacities

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Abstract

In direct job creation schemes, unemployed individuals at risk of permanent labor market exclusion are offered temporary subsidized employment in public or non-profit sector firms in combination with skills training and socio-pedagogical support. The main aim is to stabilize and qualify them for later re-integration into the regular labor market. Exploiting exogenous regional variation in population-group-specific program capacities, I find evidence that such a job creation scheme is, on average, effective in providing a bridge to a regular job. The achieved integration is, however, often not stable. Successful participants face a high risk of once again becoming unemployed.

Key Words: Active labor market policy, direct job creation, IV estimation, travel time distances, regional variation • *JEL-Codes:* C26, J08, J68

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1 Introduction

Even in the countries with the lowest unemployment rates, there are segments of individuals with severe difficulty gaining a foothold in the regular labor market. Often these people face multiple employment obstacles, such as long periods of joblessness, a lack of qualifications, disability, and social problems. As a consequence, they seem to have few prospects of finding a regular job, and conventional modes of public employment assistance reach their limits. Direct job creation schemes (JCS) have emerged as an alternative policy tool to help these individuals at risk of permanent labor market exclusion. In such a measure, unemployed workers are provided with temporary subsidized jobs in autonomous public or non-profit sector enterprises, that trade in the market but serve social needs. The main aim is to stabilize and qualify them for later re-integration into the regular labor market. In this article, I evaluate the impact of participating in an Austrian JCS that combines subsidized employment in a relatively sheltered environment with training and socio-pedagogical support. I assess whether the program is effective in providing a bridge to a job in the regular labor market.

Previous evaluations of direct job creation in the public or non-profit sector tend to find that this measure has an insignificant or even adverse impact on post-program employment outcomes (cf. Card – Kluve – Weber 2010, Kluve 2010). However, most of these studies apply empirical strategies, such as a matching approach, that critically rely on the selection-on-observables-assumption. Due to their focus on the most disadvantaged groups in the labor market, correction for selection bias is particularly vital for an assessment of direct job creation schemes. It is not clear, whether all the relevant variables can be observed that capture this "negative" selection of individuals into the program. In contrast to earlier research, I propose an instrumental variable (IV) approach to cope with the potential endogeneity of participation. More specifically, I exploit exogenous regional variation in target-group-specific program capacities to identify program effects.

Program capacities are distributed very unequally across Austrian regions and population groups. As a consequence, similar people who live in similar neighborhoods and economic environments are exposed to different program participation probabilities. This regional variation can plausibly be assumed to be exogenous, if confounders at the individual and the regional level are appropriately controlled for. My identifying instrument is the target-group-specific program capacities in the vicinity of an unemployed person. To determine the program capacities nearby, I calculate the travel time distances between zip code areas of residence and program locations based on Google Maps. In addition to socio-demographics, employment histories, previous participation in labor market programs, and contact intensity to the Public Employment Service, I control for numerous aspects of the job-seekers' home-region, especially indicators of the local labor market and the local business conditions. This way I deal with the potential endogeneity of job-seekers' and enterprises' location choices.

My empirical results confirm that effectively helping the program participants back into regular employment is a difficult challenge. I find no clear evidence that individuals are successful in gaining a foothold in the labor market on a long-term basis. However, on average, unemployed individuals benefit from participation in terms of a higher transition rate from unemployment to regular employment and a stronger labor market attachment over a four-year follow-up-period. In this sense, the program can act as a stepping stone out of joblessness.

2 The Austrian Job Creation Scheme

Austrian active labor market policy covers a broad spectrum of measures (see Eppel – Mahringer 2013 for an overview). The job creation scheme of interest is targeted at the most disadvantaged individuals: unemployed individuals who lack the prospect of a regular job, because they are faced with special – often co-occurring – employment handicaps, such as long-term unemployment, higher age, disability, care duties, lack of labor market skills, and social problems (f.i. former drug addiction, imprisonment or homelessness). The goal is to integrate these hard-to-place workers into the regular labor market through the provision of near-market yet largely sheltered fixed-term jobs. Employment is provided under a formal employment relationship mainly by non-profit social enterprises producing goods or rendering services useful for society. Typically, these are established in low-skill industries and occupations, such as maintaining parks and green spaces, interior and exterior refurbishing, gastronomy, transportation, scrap and junk recycling, textiles, wood and metal processing, sale of second-hand goods, cleaning, household and home services. Subsidized employment is usually accompanied by targeted skills training and socio-pedagogic support. This can include targeted outplacement services, such as assistance with job search and job applications, as well as some follow-up assistance.

Prior to entering employment, participants may attend a preparatory program that can last up to eight weeks. It includes work training and work trials, in which the candidates' aptitude for the intended job is tested. Sometimes it is complemented by some qualification module. The legal program guidelines foresee that more than 50 percent of the participants of a preparatory program will enter subsidized employment. Maximum duration of the actual program is twelve months, but it may be extended in certain cases. Older unemployed workers who are about to enter retirement (in 3.5 years or less) and have no formal job prospects are an exception. They may remain in subsidized employment until retirement under certain conditions.[1]

Assignment to the program is determined by the caseworkers of regional employment offices on the grounds of need. They allocate unemployed individuals to a specific program location – under assessment of the local labor market conditions and the person's employment prospects, deficits and needs. Social enterprises providing temporary work places have limited control over who works for them. They can only choose which of the participants of their preparatory program may enter subsidized employment.

There are two types of social enterprises, which are very similar in their design: "Socio-economic Enterprises" (SEEs) and "Non-profit Employment Projects" (NEPs). The main difference between them is that, in contrast to NEPs, SEEs pursue both social and economic goals. They are set up to foster skills development and placement and receive partial reimbursement of the cost incurred for providing fixed-term employment to unemployed workers. At the same time, they are obliged to generate enough revenue to cover 20 percent or more of their expenses. This regulation is intended to ensure entrepreneurial approaches despite public funding. Unlike SEEs, NPEs are not required to earn any revenues and are therefore not in standard competition with real business companies. NEPs willing to hire jobless people for a fixed term receive financial support from the Public Employment Service (PES) in the form of wage subsidies amounting to 66.7 percent of wage costs (in justified cases up to 100 percent). In addition, the staff costs for key workers of the project are fully covered throughout the entire program period, with such staff including qualified project managing and operating staff, skilled trainers and supervisors or social workers needed to assist project participants. The same applies to overheads and to costs incurred in preparing the project. Both types of social enterprises are financed primarily by the PES, usually in contracts approved for one year. Supplementary funding can be obtained from the provincial and local governments as well as the European Social Fund (ESF) and other (semi-)public institutions (cf. Federal Ministry of Labour, Social Affairs and Consumer Protection 2013a, 2013b). Since they are so similar in their actual design, I do not differentiate between the two forms of social enterprises in the evaluation.

3 Data and descriptives

3.1 Data and sample

My empirical analysis is based on two merged sources of administrative data: the Austrian Social Security database (ASSD) and the Austrian unemployment register (AUR). The ASSD is a matched firm-worker data-set that provides a full record of labor market histories and earnings of all private-sector workers in Austria on a daily basis from 1972 onwards. I use it to control for individuals' previous employment histories and to derive all outcome measures. From the AUR, I obtain extensive information on the socio-economic characteristics of all unemployed individuals registered at the Public Employment Service (PES), their participation in labor market programs, transfer payments received, and contact to the PES. All region-specific data on incidence and structure of unemployment are drawn from the AUR as well. Supplementary data on local business conditions are obtained from Statistics Austria.

My sample comprises adult individuals aged 25-59 years who live in Austria and have either been registered as unemployed (including those searching for an apprenticeship) or entered the program of interest in the year of 2008 and remained in it longer than a month (31 days). Persons under the age of 25 are not part of the sample, because for them I cannot be sure to observe enough information on potential confounders. People who are older than 59 years are excluded from the analysis to avoid interference with possible (early) retirement. In 2008, the regular retirement age was 65 for men and 60 for women in Austria.

I summarize a sequence of two or more subsidy cases into a single program episode, if the time distance between them did not exceed a month. Only program episodes that last longer than 31 days are evaluated. The reason is that shorter episodes often end after a preparatory period without a subsequent employment relationship. To isolate the effect of participation in the program and time of interest, I exclude 31,161 people from the analysis who worked in some type of subsidized employment in the last six months preceding the start of the program. Individuals who participated in some other labor market measure prior to program entry are not excluded. However, I control for participation in a range of programs in the last half-year and the past three years in the estimations.

I additionally exclude treated individuals with a recruitment promise (228,437), observations with missing information on regional characteristics, place of residence, labor market district or (in the case of program participants) program location (2,644), as well as workers for whom federal state of residence and state of the responsible Public Employment Office are not consistent in the data (1,078). My final data set has 658,341 observations, of which 4,367 are treatment (0.66 percent) and 653,974 are comparison observations (99.34 percent). The full sample includes 473,157 individuals.

My data-set is structured such that each individual appears once in every half-year, in which he or she was unemployed or entered the program. Treatment and comparison groups are defined semi-annually: Unemployed individuals who entered the program during a specific half-year are perceived as the treated, those who did not are defined as the non-treated. This half-year classification-window is to assure the similarity of the macro-economic conditions during participation.

Treatment effects are measured from program entry. To each non-participant I assign a hypothetical starting date, which is located in the middle of a person's unemployment phase in a half-year. Rather than evaluating program effects at an arbitrary point in time, I measure outcomes over a four-year follow-up-period (2008-2012). In this way I capture the dynamic of the labor market and the sustainability of effects.

My primary aim is to test whether the program is effective in providing a bridge to successful integration into the regular labor market. To this end, I neglect the first year of the follow-up period, in which most program episodes end. I measure effects only in the time period between the second and fourth year after (hypothetical) program entry. This is to mitigate the problem of "locking-in effects" (Van Ours 2004): During program participation unemployed individuals are "locked-in" to the subsidized job.

3.2 Outcome variables

Outcomes are measured in terms of several labor market indicators that are all calculated from the ASSD. Most importantly, I assess the number of cumulated days spent in regular dependent employment. This measure includes apprenticeships and subsidized employment in the first labor market (employment supported in the form of hiring subsidies or a combination wage), but excludes subsidized temporary employment in a social enterprise (second labor market). It is restricted to employment with earnings above the marginal earnings threshold and further excludes self-employment and atypical employment in the form of contract-based work and freelance employment.

As a second outcome, I use the number of days spent in registered unemployment, which is defined in a broad manner and includes participation in skills training for job-seekers as well as periods in receipt of sickness benefits. Furthermore, I assess outcomes in terms of the number of cumulated days spent outside the labor force (OLF). This category includes both individuals who have a job but are temporarily out of work (e.g. on parental leave) and those entirely outside the labor force. I distinguish between OLF-times with and without receipt of social protection based on own contributions, such as parental leave payments and old-age pension, to better grasp the individuals' social situation. In fact, old-age and invalidity pension account for the majority of days outside the labor force with social protection. I therefore separately report outcomes in terms of cumulated pension times.

Only in my least-squares regressions do I estimate program effects on days spent in subsidized employment (temporary work in a social enterprise), because this outcome is very likely to be directly affected by my instrument. To test whether participation in the job creation scheme facilitates the transition from unemployment to regular employment, I specify dummies that equal unity, if an individual was employed in a regular job for (1) at least one day, (2) more than three months and (3) more than six months, respectively.

Summary statistics for all outcomes are presented in Table 1. In the full sample, the average number of days spent in regular, dependent employment in the time between the second and fourth year after program start is 461. This corresponds to a proportion of 42.1 percent of all calendar days. Before conditioning on control variables, program participants seem to be much less integrated into the regular labor market than their non-participating counterparts, with a mean of 278 days (25.4 percent) compared to 462 days (42.2 percent). They spend less time outside the labor force (89 days compared to 144 days). At the same time, they are much more in unemployment, with the mean at 575 days compared to 326 days. The transition rate to regular employment, measured by the share of individuals with (1) at least one day, (2) more than three months and (3) more than six months in a regular job is always lower for the participants.

Table 1: Summary statistics on outcomes

	(1) Full sample	(2) Program participants	(3) Non-participants
Days in regular employment	461 (429)	278 (362)	462 (429)
Days in unemployment	328 (359)	575 (377)	326 (358)
Days OLF	247 (377)	182 (314)	247 (377)
Days OLF with social protection	104 (278)	93 (257)	104 (278)
Days OLF without social protection	143 (292)	89 (209)	144 (293)
Days with pension benefits	83 (262)	78 (243)	83 (262)
Days in subsidized employment	6 (38)	47 (106)	6 (37)
$\geq$1 day in regular employment	0.70 (0.46)	0.64 (0.48)	0.70 (0.46)
>3 months in regular employment	0.63 (0.48)	0.48 (0.50)	0.63 (0.48)
>6 months in regular employment	0.59 (0.49)	0.41 (0.49)	0.59 (0.49)

Sources: ASSD and PES data. Notes: Mean values for the time between second and third year after program entry. Standard deviations are displayed in parenthesis.

3.3 Treatment and control variables

The primary right-hand variable in my empirical analysis is a binary treatment indicator that equals one, if a given individual participated in the job creation scheme. In addition to program participation and an indicator for the half-year observed, the empirical model includes a number of exogenous socio-demographic characteristics that might be correlated with employment outcomes, namely gender, age (in years), marital status, number and age of dependent children (in the case of women), a dummy for having a migration background, nationality, the level of the highest completed education, and disability status. Furthermore, I include a binary indicator for whether an individual was returning into the labor market after a family-related career break as well as information on the level and type of the last unemployment insurance benefit received. All these data stem from the AUR.

A second block of control variables relates to individuals' labor market histories and is calculated on the basis of the ASSD. It includes the duration of joblessness, attributes of the last job (last occupation, economic sector, and last monthly earnings) as well as detailed employment histories over the 15 years prior to (hypothetical) program entry: the number of employment and unemployment spells (in the last two years) and times spent in various forms of employment, unemployment, and outside the labor force. As supplementary indicators I consider the times of sickness benefit receipt during employment and unemployment.

Both participation and employment outcomes may further be affected by previous experiences with subsidized employment, participation in other active labor market programs, as well as the frequency of contact to the PES. I account for these aspects by incorporating into the model a third block containing the number of contacts with the PES and the number of placement offers received by the PES as well as the frequency of participation in various types of labor market programs prior to (hypothetical) program entry. This information is extracted from the AUR.

A fourth block of control variables consists of numerous neighborhood characteristics. One part of them is measured at the labor market district level (geographical areas that are each served by a regional employment office) and includes the region type (classified into human-capital intensive, physical-capital-intensive and rural), as well as several indicators of the local labor market conditions and the presence of individuals with labor market difficulties: the unemployment rate by gender and age group (in 5-years-intervals), the share of long-term unemployed, the average level of unemployment insurance benefits by gender, and the gender-specific ratio of unemployed per job vacancy. To control for the educational structure of unemployment, I add the respective shares of unemployed workers with low education (compulsory school or less), medium education (apprenticeship, intermediate vocational school) and higher education (higher academic or vocational school or tertiary education). Moreover, I include the share of individuals with disabilities among the unemployed.

Another part of control variables at the regional level consists of aspects that reflect the local business conditions and, thus, may affect firm entry and location decisions. More specifically, I incorporate in my empirical model indicators of the general economic conditions, the competition level, and consumer demand. I control at NUTS-3-level for the total number of active enterprises and the number of workers in active enterprises, the Gross Regional Product (GRP) per capita (at current prices), and the Gross value added at basic prices (in Mio. €) by economic sector in 2008. Furthermore, at the labor market district level I add the number of active enterprises by industry (ÖNACE 2008-section) in 2011 and the population density in 2001. All these data on local business conditions are obtained from Statistics Austria, more specifically the Statistics on employer business demography 2008, the Regional accounts 2008, the Register-based census 2011, and the Population census 2001.

In addition to the regional characteristics at the labor market district and the NUTS-3-level, my model contains dummies for the federal state in which individuals reside. This is to account for unobserved policy, economic, and demographic confounders on the federal state level. All control variables are unaffected by participation, as they are fixed over time or measured before participation: at the time of actual or hypothetical program entry.

3.4 Descriptives

As revealed by Table 2, at least part of the differences in labor market integration between the program participants and the non-participants can be attributed to a negative selection of individuals with inferior labor market prospects into the program. Summary statistics on selected controls (for a full list see Table 7 in the Appendix) reflect the policy priority placed on individuals with major employment obstacles, namely a higher age, low qualification, disability, child-care obligations, and a long record of joblessness:

- The participation probability rises with age. People aged between 45 and 54 years have the highest participation rate (0.86 percent).
- Individuals with compulsory schooling or an apprenticeship as their highest educational attain-

ment account for almost two thirds of all program episodes (62.2 percent). This quantitative importance is not only due to the high sample share of this group among the unemployed (48.4 percent), but also a disproportionately high participation rate (0.85 percent). By contrast, workers with high education (higher academic or vocational school or academic education) account for only 6.2 percent of the participants and have a participation rate of 0.32 percent.

- Program participants suffer more frequently from health problems, as indicated by the times of sickness benefit receipt and disability status. The proportion of people with disabilities among the participants (31.5 percent) is twice the share among the non-participants (14.6 percent). At 1.42 percent, the participation rate is twice the average for the full sample (0.66 percent).

- Returning to the labor market after a family-related career break seems to increase the odds of receiving treatment. This group accounts for 8.8 percent of all treated persons and has a participation rate of 1.09 percent.

- The participation rate rises with the number of days spent in unemployment or out of the labor force in the past. Participants and non-participants differ largely in pre-treatment outcomes. With an average of 402 days (22.0 percent of all calendar days), program participants were only half as much in regular employment than non-participants (827 days or 45.3 percent) in the five years preceding (hypothetical) program entry and almost twice as much in unemployment (934 days or 51.1 percent compared to 477 days or 26.1 percent).

- The vast majority of the participants (79.3 percent) received unemployment assistance at the time of program entry. This is a means-tested type of benefit payable on expiry of entitlement to unemployment benefit. By contrast, nearly two thirds of the non-participants (67.3 percent) received the higher unemployment benefit paid to unemployed workers in the first instance.

In their last job, program participants earned, on average, a significantly lower monthly income. Measured by the observed assessment basis for social security contributions up to the maximum under social insurance law (excluding extra payments), it amounted to €1,220 – compared to the average of €1,524 for non-participants. The participants were more often in labor market programs and had twice as much contact to the PES (8 contacts in the last 6 months, 24 in the last two years) than the non-participants (4 and 12 contacts, respectively) in the pre-treatment period. All this is strong evidence that program participation is endogenous.

Table 2: Summary statistics on selected controls

	Sample share (in %)			Participation rate (in %)
	(1) Full sample	(2) Participants	(3) Non-participants	(4) Full sample
Women	45.3	52.7	45.2	0.77
Men	54.7	47.3	54.8	0.57
Age 25-34 years	32.2	24.7	32.3	0.51
Age 35-44 years	33.1	33.0	33.1	0.66
Age 45-54 years	26.4	34.3	26.4	0.86
Age 55-59 years	8.3	8.0	8.3	0.64
Family-related returners	5.3	8.8	5.3	1.09
People with disabilities	14.8	31.5	14.6	1.42
People without disabilities	85.2	68.5	85.4	0.53
Low education	48.4	62.2	48.3	0.85
Medium education	38.7	31.6	38.7	0.54
High education	12.9	6.2	12.9	0.32
≤1,096 days jobless in last 5 y.	58.1	24.7	58.4	0.28
1,097-1,827 days jobless in last 5 y.	41.9	75.4	41.7	1.19
Unemployment assistance receipt	33.0	79.3	32.7	1.60
Total	100.0	100.0	100.0	0.66

Sources: ASSD and PES data. Notes: Low education: compulsory school or less. Medium education: apprenticeship, intermediate vocational school. High education: higher academic or vocational school, academic education. Family-related returners: individuals returning after after a family-related career break.

4 Econometric strategy

The investigated relationship between program participation and employment outcomes can be described with the following equation:

$$y_i = \beta_0 + \beta_1 p_i + \beta_2 hy_i + \mathrm{X_i}\beta_3 + \mathrm{N_i}\beta_4 + v_s + \epsilon_i, \tag{1}$$

where y_i, the dependent variable, is the labor market outcome of individual i, p_i is a binary indicator of program participation, and hy_i is the half-year observed. The vector X includes the observed determinants of labor market outcomes at the individual level, namely socio-demographics, employment histories, previous participation in ALMPs, and contact intensity to the PES. Observable neighborhood characteristics that are potentially associated with outcomes are captured by the vector N and complemented by state fixed effects, v_s, and an error term, ϵ_i.

Even though I am able to condition on a rich set of covariates, I cannot rule out unobserved heterogeneity and therefore run the risk of obtaining biased results based on an OLS estimation. To cope with this problem and to correct for a remaining endogeneity of program participation, I perform two-stage least squares (2SLS) instrumental variable regressions of the above model, with one endogenous regressor, a large set of exogenous regressors and one excluded exogenous variable that serves as my identifying instrument.

The proposed instrument builds on the fact that the availability of program places varies widely among Austrian regions and population groups and that, under certain conditions, this variation can be regarded as exogenous. Assignment to the program of interest necessitates the presence of program places in the neighborhood. In fact, there are people who live close to one or even multiple social enterprises and, hence, have a positive participation probability, whereas others live so far from the next program location that commuting is too expensive in terms of time and money and the probability of being assigned to the program virtually boils down to zero. The available enterprises vary in their size and focus on target groups. This implies that individual treatment probability is influenced by the population-group-specific program capacity nearby. Due to the profound geographical differences in treatment intensities, I find similar people who live in similar neighborhoods and under similar labor market conditions, but are exposed to different participation probabilities. I exploit this exogenous variation to construct an instrument, with which I identify the employment effects of participation in the program.

Construction of the instrument

To construct my instrument, I begin by supplementing my person data set with residential location information. Since full addresses are not available for privacy reasons, I use the approximated geographical center of the zip codes where unemployed individuals reside. In addition to the person data set, I create a database containing the precise location (street name, city, state, and zip code) of every project operated by social enterprises in Austria in 2008. Next, I split my population of unemployed into target groups along several dimensions by which treatment intensities have been shown to vary most: gender, age (in 5-year-intervals), disability status, highest completed education (low, medium, high), and extent of pre-treatment labor market exclusion (times in unemployment and out of the labor force). On this basis, I calculate the population-group-specific number of treatments starting in 2008 for each project. Furthermore, I compute the number of unemployed individuals belonging to a population group for each zip code.

I merge the information from person data set and project database into a new data-set that consists of all combinations of 2,179 residence zip codes of unemployed job-seekers and 170 projects of social enterprises. Then I geocode the locations of residence and projects by assigning a latitude and longitude coordinate to each. Finally, using the quickest route recommended by Google Maps, I compute the distances between any pair of zip codes of residence and project locations in terms of travel time by car in minutes and travel distance by car in kilometers.[2] I also provide Euclidean distances (or "As-the-crow-flies-distances") but do not use them in the empirical analysis, because travel times are likely to depend on geographical features such as waters and mountains as well as the availability of local roads and highways and the associated amount of traffic congestion. In contrast to a linear measurement of distances, driving distances account for these aspects. Clearly, not everyone commutes by car. However, since directions via public transit routes are not yet readily accessible, I rely on a strong correlation between the travel times by car and public transport. In cases where projects have several locations, it is not clear how the total number of program places is geographically allocated. For each individual (or zip code area) I calculate the distance to every project location to select the nearest one.

Based on the calculated distances between zip code centers and project locations, I construct my instrument: the (relative) target-group-specific program capacity in the vicinity of an unemployed person. This procedure consists of several steps: First, for each project and on a half-year basis I determine the population-group-specific number of unemployed individuals living in the project's catchment area, i.e. within a maximum driving distance of 20 minutes. Second, I derive a relative measure of a project's population-group-specific program capacity in a half-year, based on the program episodes starting in the observed half-year of 2008. Assuming that the individual probability of being assigned to a nearby project is influenced by the quantity of "competing" candidates for participation, I divide the absolute group-specific number of a project's program places by the number of unemployed individuals who reside in the project's catchment area and belong to the respective subgroup. Third, for each zip code and population group I determine the relative population group-specific program capacity within commuting distance (maximum travel time distance of 20 minutes by car).

My definition of what is in commuting distance is derived from the observed distribution of the actual distances between the residences of the participants and the locations of their assigned program places in 2008. As can be seen in Table 3, the mean travel time by car was about 16 minutes (median 12 minutes). The average distance to the next project is only 10 minutes for the full sample, but only a minority of the participants (29.7 percent) was assigned to the nearest one in 2008. For 75 percent of the participants, the commuting time to their project location was no longer than 20 minutes. Using this 75 percent-percentile-value as a cut-off point leads to the strongest correlation between my instrument and the instrumented variable.

Table 3: Travel time distance between residence and program location for the participants in 2008

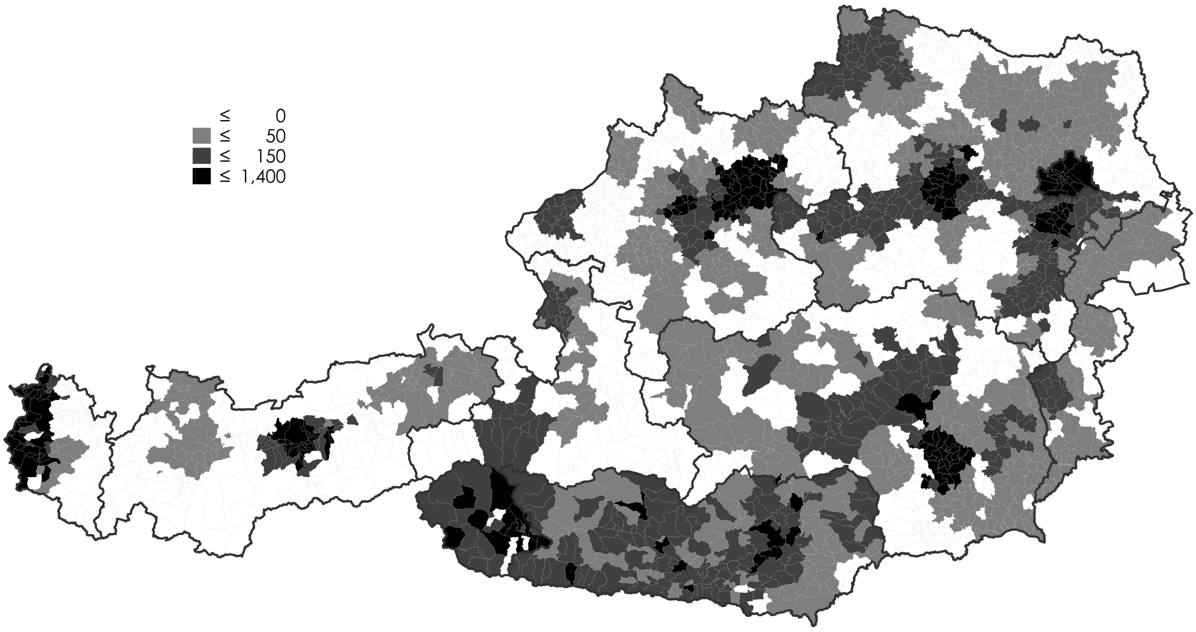
	Mean	St. dev.	Median	Min	Max	p25	p50	p75
Travel time by car (in minutes)								
Entire Austria	16	14	12	0	127	7	12	20
Excluding Vienna	16	16	11	0	127	6	11	20
Travel distance by car (in kilometers)								
Entire Austria	14	21	8	0	223	3	8	15
Excluding Vienna	16	24	7	0	223	3	7	19
Euclidean distance (in kilometers)								
Entire Austria	10	15	6	0	155	2	6	11
Excluding Vienna	12	17	6	0	155	2	6	14

Sources: ASSD and PES data.

For each person, I take into account only program places that are located in the federal state of residence, because programs are administered at this level and I observe a sharp cut-off along provincial borders: unemployed individuals are generally assigned only to projects in the federal state of their residence and regional employment service (REO). Only in six out of 4,361 cases (0.1 percent) do the federal state of residence and the state of assigned project not match in my data. In the majority of cases (84.8 percent), job-seekers are even supported in a project located within their local labor market district, i.e. the geographical area for which a REO is responsible.

Figure 1 illustrates the heterogeneity of program capacities at the regional level. It compares the absolute number of program places in the vicinity of zip code areas. For the average individual in my sample, 406 program places were reachable within a travel time of 20 minutes by car in 2008. Excluding the capital of Vienna, the mean value was 138 places. Adjusted for the number of potential candidates for participation in the catchment area of a project, the average program capacity in the vicinity was about 0.007 in Austria – seven places per thousand individuals (0.008 without Vienna). It was considerably higher for the participants (0.010) than for the non-participants in my sample (0.007).

Figure 1: Absolute number of program places in the vicinity of an individual by zip code area in 2008



Data sources: ASSD and PES data. Notes: Program places correspond to the number of program episodes starting in a given half-year of 2008 according to the Austrian unemployment Register (AUR). In vicinity: within a maximum travel time distance of 20 minutes by car.

The relationship between the population-group-specific program capacity in the vicinity and actual participation is not equally strong in all federal states. Most importantly, Vienna is an exception in that the instrument is weak for this city and federal state. Possible explanations are that many individuals do not use a car, but instead use the well-developed system of public transport and virtually all project locations can be reached at reasonable expenses in terms of time and money. To solve this problem, I modify my instrument in the case of Vienna by using the population-group-specific quota of program places per unemployed in a local labor market district. Vienna, the capital of Austria, is split into ten local labor market districts that are each served by a REO. When becoming unemployed, individuals must register with a unique REO defined by place of residence. It is up to these local authorities to determine the extent to which they make use of the available supply for temporary work places. Generally, all unemployed workers residing in Vienna can be assumed to supply their labor on a homogeneous labor market. At the same time, they are exposed to different likelihoods of being assigned to the job creation scheme, because REOs differ in the intensity with which they use this program. In other words, policies change abruptly when the borders of local labor market districts are crossed, but economic environment and likelihood of program participation do not. Thus, regional borders may be interpreted as acting like an instrument which can be used to estimate policy effects (cf. Frölich – Lechner 2010). I follow this idea in the special case of Vienna by instrumenting program participation with the population-group-specific quota of program places per unemployed in the local labor market district of residence.

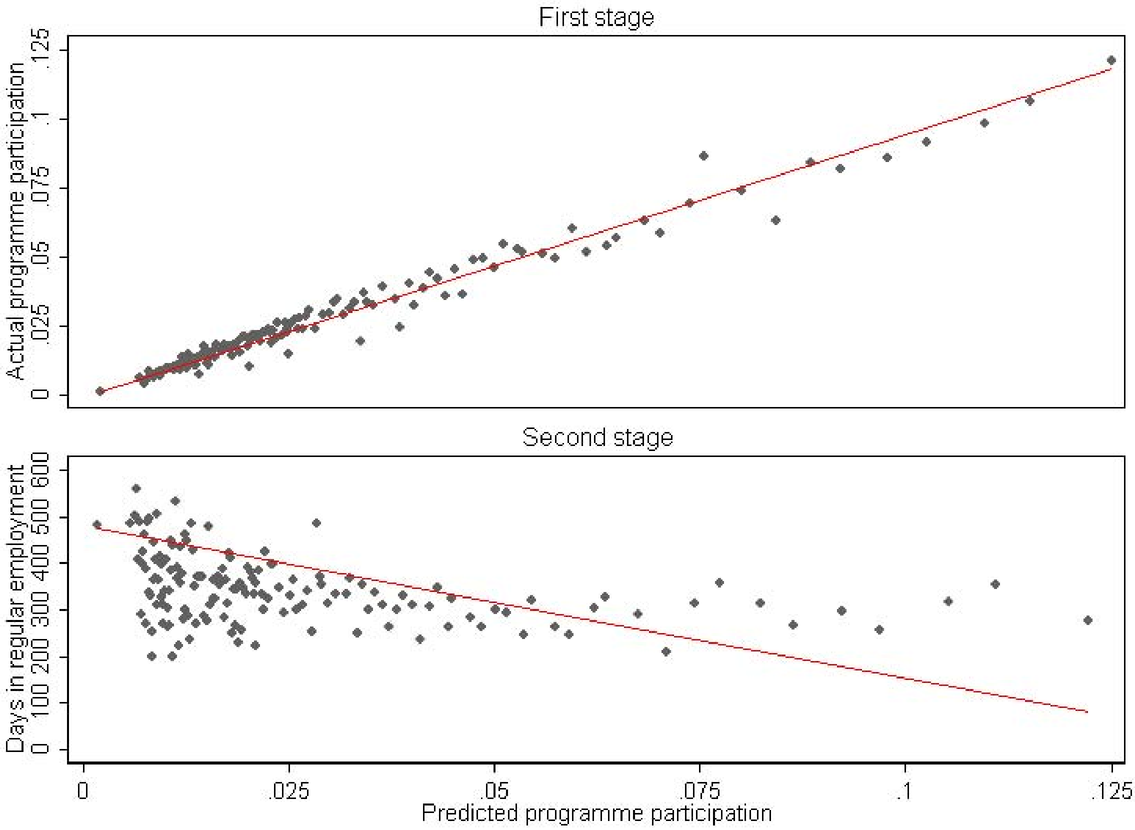
Plausibility of the instrument

In order to be valid, my instrument must satisfy two requirements. First, it must be partially correlated with individual program participation (instrument relevance). Second, it must be exogenous in the sense that it is uncorrelated with any unobserved determinants of labor market outcomes in the error term of equation (1).

To demonstrate the instrument's relevance, in the top graph of Figure 2 I visualize the first-stage relationship between program participation as predicted by the target-group-specific program capacity in vicinity (x-axis) and actual treatment incidence (y-axis). More specifically, I plot the mean of the observed treatment status (virtually the share of treated) on group means obtained from the predicted probability of participation. Clearly, this graph shows a positive correlation, indicating that individual treatment probability increases with the target-group-specific program capacity nearby. The first-stage regression of the binary endogenous indicator of program participation on the identifying instrument and all exogenous regressors appearing in the structural equation has reasonable explanatory power. The F-statistic on the excluded instrument is 1,786, and the coefficient is positive and highly statistically significant, with a t-statistic of 42.26 and a p-value that is zero in the first three decimals.[3] Thus, my instrument is strongly relevant for explaining variation in program participation.

The bottom graph shows a variant of the second-stage IV regression that uses group mean values of predicted participation on the x-axis and the number of days in regular employment on the y-axis. Not surprisingly, the raw correlation between target-group-specific program capacity in vicinity and employment outcomes is negative. Based on the descriptive summary statistics it is clear that this negative association is, at least partly, driven by a negative selection of individuals into treatment that has to be controlled for in the IV estimation. In my empirical framework, the exogeneity requirement is satisfied only after conditioning on the covariates specified in equation (1).

Figure 2: Visual instrumental variables (VIV) plot



Data sources: ASSD and PES data. Notes: The top graph plots the mean of the observed participation status (*y-axis*) on group means obtained from the predicted probability of participation (*x-axis*). The bottom graph plots mean days in regular employment (*y-axis*) on group means of predicted participation (*x-axis*). 200 groups are constructed: one group including all zeros (86.1 percent) and another 199 percentile groups (summing up to 13.9 percent).

There are basically four concerns as to the exogeneity of the proposed instrument. One is that location choices could be endogenous in the sense that unemployed individuals non-randomly choose to live in areas with a higher target group-specific program capacity. Highly motivated workers or individuals in particular need of a job may change residence, because they expect to increase their probability of being assigned to the program and consequently their chance of finding a regular job. A second concern could be selective location choices by social enterprises that are not orthogonal to individual characteristics relevant for labor market outcomes. More specifically, social enterprises may concentrate in regions with unfavorable labor market conditions or more people in need of support. A third concern could be that social enterprises choose to settle where they find the most productive unemployed workers in order to maximize firm performance. Finally, a fourth concern is that the supply with program places is possibly correlated with other regional parameters that affect employment outcomes, such as the local business cycle, the labor market conditions or the availability of education and training. A particular example is that travel times could vary by the type of region. For instance, unemployed individuals living in largely rural or mountainous areas may have a smaller number of program places in a 20 minute-travel-time-distance than those living in a flat or urban region with easy roads. To the extent that aspects of the neighborhood environment such as the type of region are associated with labor market opportunities, the program capacity measure may be systematically related to these outcomes.

Endogenous residence choices from the side of unemployed individuals are intuitively not very plausible. In cases when the available program capacities are actually considered a motive for the choice of a home location, people would need to gather information on regional and group-specific differences in treatment intensities, which is difficult to access. Moving to another neighborhood can be costly and troublesome and entails a large degree of uncertainty as to the actual opportunity of participating in the program and the potential returns. Selective location decisions seem to be more plausible for social enterprises. It may actually be that regional employment offices use the job creation scheme more intensively in areas with a greater need for this kind of treatment – in regions with relatively poor labor market conditions and a high concentration of potential clients. To guard against the confounding effect of such endogenous location choices of unemployed individuals or enterprises as well as of neighborhood differences, I incorporate in my empirical model not only a rich set of individual characteristics, but also numerous aspects of the job-seekers' home region, especially indicators of the local labor market conditions and the presence of individuals with (severe) difficulties of finding a job. Based on this set of covariates, I only compare similar people who live in similar regions and under similar labor market conditions.

Selective location decisions in favor of regions with more productive unemployed workers do not seem very plausible for two reasons: First, subsidized employment is provided mainly by non-profit social enterprises that are explicitly designed to serve a social purpose: to support marginalized individuals with reduced productivity in regaining the capabilities needed for a successful reintegration into regular employment. That is what distinguishes them clearly from profit-maximizing firms. Second, social enterprises have only limited control over who works for them, since it is the caseworkers of the PES who assign job-seekers to program locations. Nevertheless, a sorting of individuals or firms based on unobservable characteristics cannot be ruled out. To account for the fact that firm entry and location decisions are usually influenced by the local business conditions, I control for several regional aspects that possibly affect the expected success of a firm. These include the general economic conditions, the competition level, and consumer demand.

5 Empirical results

Table 4 presents the estimated effects of participating in the job creation scheme on subsequent labor market outcomes. I first present coefficients on program participation from several OLS regressions. The fullest OLS specification, presented in column (4), includes individual characteristics (socio-demographics, labor market histories, previous participation in labor market programs and contact to the PES), neighborhood characteristics (region type, local labor market and business conditions), and state fixed effects. It is contrasted with the IV estimates for the same specification, which are depicted in column (5).

Clearly, the differences in OLS results by model specification reveal the negative selection of individuals with inferior labor market prospects into the program. Before conditioning on covariates, the estimated coefficient on participation is -184 and, thus, very negative. It indicates that program participants are, on average, half a year less in regular employment than non-participants in the follow-up-period (full sample mean: 461 days). Once I control for individual characteristics in the model (including pre-treatment outcomes), the effect turns positive. This implies that the negative outcome in a comparison of raw means is fully driven by the unfavorable labor market attributes of the treated.

Table 4: OLS and IV estimates of the effect of program participation on employment outcomes

Outcome	OLS				2SLS
	(1)	(2)	(3)	(4)	(5)
Regular employment	-184***	12**	9*	9*	60***
	(6)	(5)	(5)	(5)	(19)
Unemployment	250***	64***	71***	71***	85***
	(6)	(5)	(5)	(5)	(19)
OLF	-66***	-60***	-63***	-64***	-163***
	(5)	(5)	(5)	(5)	(21)
OLF with social protection	-11***	-23***	-26***	-26***	-124***
	(4)	(4)	(4)	(4)	(18)
Pension receipt	-6	-21***	-23***	-23***	-115***
	(4)	(4)	(4)	(4)	(17)
OLF without social protection	-55***	-36***	-37***	-38***	-39***
	(3)	(3)	(3)	(3)	(14)
Subsidized employment	41***	29***	28***	28***	
	(2)	(2)	(2)	(2)	
Half-year control	x	x	x	x	x
Individual controls		x	x	x	x
Neighborhood controls			x	x	x
State fixed effects				x	x

Sources: ASSD and PES data. *** p<0.01, ** p<0.05, * p<0.1. Notes: 658,341 observations. Outcomes are expressed in days. Robust standard errors in parentheses. No 2SLS-estimates of subsidized employment, because of correlation between instrument and outcome.

Adding neighborhood characteristics and state fixed effects does not substantially alter the results. According to the fully specified OLS model, program participants spend about 9 days more in regular employment than non-participants – an estimate that is statistically significant at a 10 percent significance level. Thus, the estimates point to a very weak positive association between program participation and regular employment. Unemployment is indicated to increase by 71 days in the time period between the second and the fourth year after (hypothetical) program entry (full sample mean: 327 days), whereas time spent out of the labor-force decreases by 64 days according to the OLS estimates (full sample mean: 247 days). The OLS results point to a sustainable lock-in-effect: Even after the first year, in which most program episodes end, participants are significantly more in subsidized employment than non-participants. It seems that people who are treated once have an increased likelihood of being treated again.

Not surprisingly, the IV standard errors are much larger than the OLS ones, but the coefficient on program participation is statistically significant for all outcomes. The IV estimates have the same sign as the OLS estimates in each case. However, they differ in size. More specifically, they suggest larger positive effects of program participation on employment. Based on the 2SLS-procedure, I find that participants spend, on average, two months (60 days) more in regular labor market employment compared to the hypothetical case of non-participation. Parallel with employment, times spent in registered unemployment increase by 85 days as a consequence of a treatment, while at the same time participants spend 163 days less outside the labor force. These results unequivocally suggest that program participation strengthens labor market attachment. A major part of this effect on labor force participation is manifested through a decrease in times with receipt of an old-age or disability pension (113 days). This indicates that program participation induces older people to postpone outflow from the workforce to (early) retirement.

Table 5: OLS and IV estimates of the effect of program participation on the probability of regular employment, by gender

	OLS			2SLS		
	Total	Men	Women	Total	Men	Women
≥1 day	0.080***	0.073***	0.082***	0.168***	0.100***	0.201***
	(0.007)	(0.010)	(0.009)	(0.025)	(0.037)	(0.034)
>3 months	0.038***	0.011	0.057***	0.091***	0.007	0.139***
	(0.007)	(0.010)	(0.010)	(0.025)	(0.036)	(0.034)
>6 months	0.023***	-0.001	0.039***	0.071***	-0.016	0.120***
	(0.007)	(0.010)	(0.010)	(0.025)	(0.036)	(0.034)
N	658,341	360,292	298,049	658,341	360,292	298,049

Sources: ASSD and PES data. *** p<0.01, ** p<0.05, * p<0.1. Notes: Robust standard errors in parentheses.

As can be seen in Table 5, the probability of being at least one day in regular employment in the follow-up period increases by 17.1 percentage points as a result of program participation according to the IV estimates. The chance of being regularly employed for more than three months is estimated to increase by 9.3 percentage points, and the chance of being in regular employment for more than six months by 7.1 percentage points. There are notable gender differences with respect to this bridging effect. At 20.5 percentage points, the increase in the probability of at least one day of regular employment is twice as large for women as it is for men (10.1 percentage points). Only for women do I detect a statistically significant positive impact on the likelihood of being regularly employed for more than three months.

The comparison of OLS and IV estimates suggests that my OLS estimates are biased towards zero. A possible explanation is that – despite the rich set of observables used – some unobserved heterogeneity remains, which I am only able to control for by way of my IV estimation. It seems reasonable that with OLS the true return from participation is underestimated, because in this way the negative selection of individuals with inferior labor market prospects is not fully controlled for. An alternative explanation is that, in the presence of heterogeneous returns, the OLS and IV estimates measure different sorts of treatment effects. In contrast to OLS, IV does not identify average treatment effects (ATE) for the total population, but rather a Local Average Treatment Effect (LATE), which corresponds to the impact for those whose participation behavior is altered through changes in the instrument (cf. Imbens – Angrist 1994, Angrist, Imbens – Rubin 1996). I estimate treatment effects for the sub-population of "compliers" who only participated because they lived in a neighborhood with a high enough target-group-specific program capacity, not for "Always-takers" or "Never-takers".

Robustness checks

My results are robust to several sensitivity checks. One potential threat to the validity of my instrument could be that the capacity of program places is in some way related to the overall structure of active labor market policies (ALMPs) in a region, which itself plausibly influences labor market outcomes. In a first robustness analysis, I account for this factor by adding the participation rates in qualification measures and the Austrian private sector wage subsidy scheme as control variables to my model. As shown in Table 6, this modification hardly changes my coefficients.

In the construction of my instrument, I choose different approaches for Vienna, Austria's capital, and the rest of the country. Generally, I use travel times by car to define a neighborhood. Only in the exceptional case of Vienna do I exploit the geographical borders of a labor market district served by a Regional Employment Office for this purpose. Larger standard errors seem to indicate that my instrument is not as strong for Vienna as it is for the rest of Austria, whether I use commuting times or geographical borders. As a second robustness check, I therefore provide estimates of IV regressions for Austria without the subset of individuals residing in Vienna. This sensitivity analysis also does not alter my general findings.

Table 6: Robustness checks: IV estimates of alternative model specifications

Outcome	Total	With ALMP structure	Without Vienna	25 minutes distance	30 minutes distance
Regular employment	60***	61***	59***	54***	50***
	(19)	(19)	(21)	(19)	(19)
Unemployment	85***	84***	70***	99***	111***
	(19)	(20)	(21)	(20)	(21)
OLF	-163***	-163***	-150***	-175***	-189***
	(21)	(21)	(24)	(21)	(22)
OLF with protection	-124***	-123***	-108***	-140***	-148***
	(18)	(18)	(20)	(18)	(19)
Pension receipt	-115***	-115***	-106***	-133***	-140***
	(17)	(17)	(19)	(17)	(18)
OLF without protection	-39***	-40***	-42**	-35**	-41***
	(14)	(14)	(16)	(15)	(15)
N	658,341	658,341	444,617	658,341	658,341

Sources: ASSD and PES data. *** p<0.01, ** p<0.05, * p<0.1. Notes: Outcomes are expressed in days. Robust standard errors in parentheses.

In a third and final sensitivity analysis, I test whether my results are affected by a different choice of the maximum commuting distance by car for the definition of a neighborhood. I consider the target-group-specific program capacity within a commuting distance of 20 minutes. This could be too strict a radius and exclude relevant program places, since for a minority of actual participants I observe a travel time above this ceiling. I counter this concern by setting the limit at 25 or 30 minutes. This slightly weakens the strength of my instrument and does not lead to fundamentally different outcomes, as shown in Table 6.

6 Conclusion

I exploit exogenous regional variation in population-group-specific program capacities to estimate the effects of participating in an Austrian direct job creation scheme. In this scheme, unemployed individuals at risk of permanent exclusion are temporarily employed in public or non-profit social enterprises that offer goods and services in the market, but serve social needs. The main objective is to remove – often co-occurring – employment obstacles and to stabilize and qualify workers for later re-integration into the regular labor market. I assess whether the job creation scheme actually works in providing a bridge to a regular job.

Previous micro-level evaluations of direct job creation in the public or non-profit sector tend to find that these measures have an insignificant or even adverse impact on post-program employment outcomes (cf. Card – Kluve – Weber 2010, Kluve 2010). In contrast, I find evidence that temporary subsidized employment in a social enterprise can act as a stepping stone out of joblessness. It strengthens subsequent labor market attachment and significantly increases the entry-chance into the regular labor market, particularly for women. A possible explanation for this deviation from earlier findings is that with my IV approach I am able to fully control for the strong negative selection into the program, a condition not necessarily achieved with other identification strategies.

With an average of two months in a period of three years, the estimated program effect on regular employment is rather moderate. This may be attributed to the fact that the program is designed for the groups of unemployed individuals who are furthest from the labor market and, thus, tend to have little chance of finding a regular job. Those who are more job-ready, are typically supported via other measures that aim at a direct placement in the regular labor market.

My results suggest that subsidized employment can provide a bridge into a regular job, but I find no clear evidence that program participants succeed in gaining a foothold in the regular labor market on a long-term basis. Rather, it seems that integration is often not stable. Even after participation, individuals spend on average 575 days in unemployment (within a period of three years). In addition, they have an increased likelihood of participating again in the program at a later point of time. This implies that measures to reduce the risk of re-entering unemployment are a critical program feature. More comprehensive follow-up assistance could make it easier to recognize and counter the risks of job loss at an earlier stage. The favorable effect of program participation may be more sustainable if job coaching, vocational and socio-pedagogic support is provided at the work site or off-site after a successful transition into the regular labor market.

Due to the multifaceted nature of their problems, some of the program participants have no realistic prospect of entering regular employment. For them, permanent employment in a "second labor market" could be a sensible measure of last resort. The reason is that the potential benefits of the job creation program go beyond the net effect on regular labor market reintegration.

First, it may enable individuals to obtain a valuable work experience and, thus, to participate in social life. Second, it can prevent further human capital depletion and enhance employability through qualification, training, and the opportunity to exercise and develop individual capabilities. Third, program participants produce products and services that are of public interest and would sometimes not be available otherwise (cf. de Koning 2007).

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Appendix

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Table 7: Summary statistics

	(1) Full sample	(2) Program participants	(3) Non-participants
Outcome variables			
Days in regular employment	460.859 (429.322)	277.961 (362.326)	462.431 (429.473)
Days in unemployment	327.525 (358.673)	575.352 (377.080)	325.62 (357.970)
Days OLF	247.118 (376.547)	182.169 (314.256)	247.458 (376.891)
Days OLF with social protection	103.744 (277.523)	93.164 (256.975)	103.844 (277.654)
Days OLF without social protection	143.374 (292.477)	89.005 (208.921)	143.614 (292.921)
Days with pension benefits	83.274 (261.618)	77.855 (243.193)	83.345 (261.737)
Days in subsidized employment	5.943 (38.193)	47.092 (106.033)	5.661 (37.176)
$\geq$1 day in regular employment	0.699 (0.459)	0.638 (0.481)	0.699 (0.459)
>3 months in regular employment	0.631 (0.483)	0.480 (0.500)	0.632 (0.482)
>6 months in regular employment	0.589 (0.492)	0.410 (0.491)	0.590 (0.492)
Control variables			
Socio-demographics			
Female	0.453 (0.498)	0.527 (0.499)	0.452 (0.498)
Age (in years)	40.210 (9.452)	41.813 (9.098)	40.199 (9.454)
Single	0.310 (0.463)	0.393 (0.489)	0.31 (0.462)
Divorced	0.156 (0.363)	0.208 (0.406)	0.156 (0.363)
Married	0.421 (0.494)	0.297 (0.457)	0.422 (0.494)
Widowed	0.009 (0.093)	0.008 (0.090)	0.009 (0.093)
Cohabiting with partner	0.075 (0.263)	0.068 (0.251)	0.075 (0.263)
Married, but living separately	0.024 (0.152)	0.025 (0.157)	0.024 (0.152)
Marital status unclear	0.005 (0.070)	0.001 (0.026)	0.005 (0.070)
Number of children (only women)	0.468 (0.915)	0.624 (1.065)	0.467 (0.914)
Child aged 0-2 years (only women)	0.009 (0.094)	0.002 (0.047)	0.009 (0.094)
Child aged 2-7 years (only women)	0.191 (0.393)	0.189 (0.392)	0.191 (0.393)
Child aged 7-10 years (only women)	0.068 (0.252)	0.091 (0.287)	0.068 (0.252)
Returning after family-related career break	0.053 (0.225)	0.088 (0.283)	0.053 (0.224)
Austrian nationality	0.789 (0.408)	0.845 (0.362)	0.789 (0.408)
Turkish nationality	0.037 (0.190)	0.027 (0.161)	0.037 (0.190)
Nationality of former Yugoslavia	0.082 (0.274)	0.047 (0.212)	0.082 (0.274)
Other EU27-country nationality	0.055 (0.228)	0.038 (0.190)	0.055 (0.228)
Other nationality	0.037 (0.188)	0.044 (0.204)	0.037 (0.188)
Migration background	0.333 (0.471)	0.283 (0.451)	0.333 (0.471)
Naturalized	0.111 (0.314)	0.120 (0.325)	0.111 (0.314)
Disability according to PES-classification	0.123 (0.328)	0.257 (0.437)	0.122 (0.327)
Legal disability status	0.025 (0.156)	0.058 (0.234)	0.025 (0.155)
Compulsory school or less	0.475 (0.499)	0.617 (0.486)	0.474 (0.499)
Apprenticeship	0.337 (0.473)	0.279 (0.449)	0.338 (0.337)
Intermediate vocational school	0.050 (0.219)	0.037 (0.188)	0.050 (0.219)
Higher academic or vocational school	0.080 (0.271)	0.037 (0.190)	0.080 (0.271)
Academic education	0.049 (0.216)	0.025 (0.156)	0.049 (0.217)
Education unclear	0.009 (0.095)	0.005 (0.068)	0.009 (0.095)
Receipt of unemployment assistance	0.330 (0.470)	0.793 (0.405)	0.327 (0.469)
Level of last unemployment insurance benefit	25.049 (19.210)	19.603 (12.638)	25.091 (19.242)
Employment history			
Duration of joblessness	620.256 (1206.328)	830.890 (1115.639)	618.837 (1206.792)
Last monthly earnings (without extra payments)	1,521.627 (736.995)	1,220.491 (523.142)	1,523.883 (737.809)
Economic sector: Agriculture, forestry	0.007 (0.082)	0.006 (0.078)	0.007 (0.082)
Economic sector: Energy, water supply	0.007 (0.085)	0.006 (0.077)	0.007 (0.085)
Economic sector: Construction	0.119 (0.324)	0.043 (0.202)	0.119 (0.324)
Economic sector: Wholesale, trade	0.159 (0.365)	0.134 (0.340)	0.159 (0.366)
Economic sector: Accommodation, food service activities	0.113 (0.316)	0.094 (0.292)	0.113 (0.317)
Economic sector: Information, communication	0.018 (0.131)	0.007 (0.081)	0.018 (0.132)
Economic sector: Transportation	0.056 (0.229)	0.036 (0.186)	0.056 (0.229)
Economic sector: Services	0.249 (0.432)	0.320 (0.466)	0.248 (0.432)
Economic sector: Education, health, social work	0.079 (0.270)	0.177 (0.382)	0.078 (0.269)

continued on next page

	(1) Full sample	(2) Program participants	(3) Non-participants
Economic sector: Manufacturing	0.114 (0.318)	0.095 (0.293)	0.114 (0.318)
Economic sector: Public services	0.032 (0.177)	0.042 (0.201)	0.032 (0.177)
Economic sector: Others	0.048 (0.214)	0.041 (0.199)	0.048 (0.214)
Last occupation: Simple services	0.095 (0.294)	0.134 (0.340)	0.095 (0.293)
Last occupation: Hospitality industry	0.109 (0.312)	0.094 (0.291)	0.109 (0.312)
Last occupation: Health, education, culture	0.071 (0.257)	0.043 (0.204)	0.072 (0.258)
Last occupation: Legal professions	0.136 (0.343)	0.109 (0.312)	0.136 (0.343)
Last occupation: Agriculture, forestry	0.016 (0.126)	0.023 (0.151)	0.016 (0.126)
Last occupation: Production	0.382 (0.486)	0.451 (0.498)	0.381 (0.486)
Last occupation: Technical occupations	0.033 (0.178)	0.015 (0.120)	0.033 (0.178)
Last occupation: Transportation	0.053 (0.223)	0.033 (0.179)	0.053 (0.223)
Last occupation: Sales and trade	0.103 (0.304)	0.096 (0.295)	0.103 (0.304)
Last occupation: Unclear	0.003 (0.052)	0.001 (0.030)	0.003 (0.052)
Number of employment spells in last 2 years	1.777 (1.974)	1.306 (1.587)	1.780 (1.977)
Number of unemployment spells in last 2 years	1.921 (1.182)	1.913 (1.065)	1.921 (1.182)
Days in regular employment in last 2 years	309.089 (264.240)	81.872 (124.501)	310.606 (264.270)
Days in regular employment in last 5 years	824.166 (614.434)	401.681 (430.369)	826.987 (614.503)
Days in regular employment in last 15 years	2,523.801 (1,610.639)	1,872.280 (1,374.246)	2,528.151 (1,611.217)
Days in subsidized employment in last 2 years	2.901 (27.032)	23.259 (68.700)	2.765 (26.482)
Days in subsidized employment in last 5 years	7.547 (49.084)	60.878 (136.310)	7.191 (47.772)
Days in subsidized employment in last 15 years	11.092 (63.925)	83.224 (174.988)	10.610 (62.244)
Days sickness benefit receipt (in employment) in last 2 years	7.029 (32.072)	3.694 (20.015)	7.051 (32.136)
Days sickness benefit receipt (in employment) in last 5 years	13.049 (46.267)	9.755 (37.100)	13.071 (46.321)
Days sickness benefit receipt (in employment) in last 15 years	31.905 (77.640)	32.066 (70.318)	31.904 (77.687)
Days in freelance employment in last 2 years	1.964 (26.312)	0.533 (10.658)	1.973 (26.385)
Days in freelance employment in last 5 years	5.627 (58.579)	2.139 (32.272)	5.650 (58.715)
Days in freelance employment in last 15 years	11.990 (99.637)	6.218 (63.472)	12.029 (99.833)
Days in marginal employment in last 2 years	12.392 (64.768)	6.367 (41.679)	12.433 (64.893)
Days in marginal employment in last 5 years	33.725 (144.606)	20.166 (99.178)	33.816 (144.857)
Days in marginal employment in last 15 years	83.331 (280.912)	64.754 (245.473)	83.455 (281.129)
Days in self-employment in last 2 years	13.573 (79.723)	3.032 (31.667)	13.643 (79.942)
Days in self-employment in last 5 years	42.972 (205.919)	16.336 (119.474)	43.150 (206.363)
Days in self-employment in last 15 years	119.715 (509.111)	66.024 (369.570)	120.073 (509.895)
Days in unemployment in last 2 years	233.238 (218.256)	492.859 (187.202)	231.505 (217.409)
Days in unemployment in last 5 years	480.123 (468.548)	933.763 (467.520)	477.093 (467.077)
Days in unemployment in last 15 years	922.644 (963.675)	1,666.110 (1,102.246)	917.680 (960.752)
Days sickness benefit receipt (in unemployment) in last 2 years	20.374 (50.634)	28.116 (45.509)	20.323 (50.662)
Days sickness benefit receipt (in unemployment) in last 5 years	37.562 (84.208)	54.651 (84.827)	37.448 (84.192)
Days sickness benefit receipt (in unemployment) in last 15 years	59.689 (130.460)	86.737 (132.929)	59.509 (130.425)
Days OLF in last 2 years	142.832 (224.560)	97.635 (174.596)	143.134 (224.826)
Days OLF in last 5 years	415.955 (555.983)	347.797 (490.497)	416.411 (556.366)
Days OLF in last 15 years	1,798.142 (1,702.031)	1,666.341 (1,564.156)	1,799.023 (1,702.881)
PES contact and ALMP participation			
Number of PES contacts in last 6 months	4.241 (3.179)	7.927 (3.182)	4.216 (3.165)
Number of PES contacts in last 2 years	11.836 (9.431)	24.340 (9.199)	11.752 (9.377)
Number of PES placement offers in last 6 months	2.592 (4.721)	5.042 (6.559)	2.575 (4.702)
Number of PES placement offers in last 2 years	6.406 (10.916)	14.320 (16.381)	6.353 (10.851)
Active job search program in last 6 months	0.032 (0.176)	0.109 (0.312)	0.031 (0.174)
Promotion of occupational mobility in last 6 months	0.023 (0.150)	0.066 (0.249)	0.023 (0.149)
Qualification measure in last 6 months	0.119 (0.324)	0.395 (0.489)	0.117 (0.322)
Qualification subsidy in last 6 months	0.050 (0.218)	0.065 (0.247)	0.050 (0.218)
Frequency of active job search program in last 3 years	0.100 (0.364)	0.330 (0.633)	0.098 (0.361)
Frequency of promotion of occupational mobility in last 3 years	0.095 (0.377)	0.294 (0.642)	0.093 (0.374)
Frequency of qualification measure in last 3 years	0.460 (0.919)	1.493 (1.441)	0.453 (0.910)
Frequency of qualification subsidy in last 3 years	0.188 (0.603)	0.329 (0.789)	0.187 (0.601)
Frequency of private-sector wage subsidy in last 3 years	0.065 (0.292)	0.172 (0.511)	0.064 (0.290)
Frequency of job creation scheme in last 3 years	0.079 (0.375)	0.466 (0.833)	0.077 (0.369)
Frequency of youth measures in last 3 years	0.001 (0.041)	0.002 (0.055)	0.001 (0.041)
Regional characteristics at the labor market district level			
Federal state: Vienna	0.325 (0.468)	0.262 (0.44)	0.325 (0.468)
Federal state: Lower Austria	0.154 (0.361)	0.146 (0.353)	0.154 (0.361)

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	(1) Full sample	(2) Program participants	(3) Non-participants
Federal state: Upper Austria	0.137 (0.344)	0.208 (0.406)	0.136 (0.343)
Federal state: Burgenland	0.028 (0.165)	0.021 (0.143)	0.028 (0.165)
Federal state: Styria	0.140 (0.347)	0.176 (0.381)	0.140 (0.347)
Federal state: Salzburg	0.045 (0.207)	0.022 (0.145)	0.045 (0.207)
Federal state: Tyrol	0.060 (0.238)	0.045 (0.208)	0.060 (0.238)
Federal state: Vorarlberg	0.036 (0.186)	0.088 (0.284)	0.036 (0.185)
Federal state: Carinthia	0.075 (0.264)	0.031 (0.174)	0.076 (0.265)
Human-capital-intensive region	0.663 (0.473)	0.662 (0.473)	0.663 (0.473)
Physical-capital-intensive region	0.142 (0.349)	0.141 (0.348)	0.142 (0.349)
Rural region	0.195 (0.396)	0.196 (0.397)	0.195 (0.396)
Unemployment rate of women	0.061 (0.017)	0.059 (0.017)	0.061 (0.017)
Unemployment rate of men	0.071 (0.027)	0.067 (0.027)	0.071 (0.027)
Unemployment rate at age 25-29 years	0.068 (0.020)	0.066 (0.020)	0.068 (0.020)
Unemployment rate at age 30-34 years	0.065 (0.020)	0.062 (0.020)	0.065 (0.020)
Unemployment rate at age 35-39 years	0.062 (0.020)	0.059 (0.020)	0.062 (0.020)
Unemployment rate at age 40-44 years	0.061 (0.020)	0.058 (0.020)	0.061 (0.020)
Unemployment rate at age 45-49 years	0.060 (0.022)	0.057 (0.021)	0.060 (0.022)
Unemployment rate at age 50-54 years	0.065 (0.023)	0.062 (0.023)	0.065 (0.023)
Unemployment rate at age 55-59 years	0.081 (0.027)	0.076 (0.027)	0.081 (0.027)
Long-term unemployment rate	0.026 (0.020)	0.024 (0.020)	0.026 (0.020)
Share with compulsory school or less	0.473 (0.075)	0.481 (0.069)	0.473 (0.075)
Share with apprenticeship	0.340 (0.088)	0.335 (0.080)	0.340 (0.088)
Share with Intermediate vocational school	0.057 (0.018)	0.057 (0.017)	0.057 (0.018)
Share with higher academic or vocational school	0.084 (0.020)	0.080 (0.020)	0.084 (0.020)
Share with academic education	0.042 (0.02)	0.041 (0.021)	0.042 (0.020)
Share of disabled among the unemployed	0.148 (0.044)	0.157 (0.043)	0.148 (0.044)
Average level unemployment insurance benefit, women	20.374 (0.838)	20.289 (0.808)	20.375 (0.838)
Average level unemployment insurance benefit, men	24.906 (1.547)	24.972 (1.433)	24.906 (1.547)
Ratio of unemployed per job vacancy	7.331 (4.145)	7.056 (4.635)	7.333 (4.141)
Gross regional product per capita at current prices, 2008	35,641.817 (8,715.708)	35,761.530 (8,532.159)	35,641.017 (8,716.922)
Gross value added at basic prices (Mio.), 1^{st} sector, 2008	99.636 (75.275)	106.530 (82.236)	99.590 (75.224)
Gross value added at basic prices (Mio.), 2^{nd} sector, 2008	5,609.201 (4,398.346)	5,448.098 (4,087.451)	5,610.277 (4,400.331)
Gross value added at basic prices (Mio.), 3^{rd} sector, 2008	21,495.334 (23,591.326)	18,913.090 (21,965.120)	21,512.577 (23,600.875)
Nr. of active enterprises, 2008	42,323.612 (43,815.670)	37,268.593 (40,863.910)	42,357.368 (43,832.782)
Nr. of workers in active enterprises, 2008	374,829.169 (395,012.818)	335,098.512 (366,795.217)	375,094.476 (395,181.308)
Participation rate, qualification	0.165 (0.054)	0.167 (0.049)	0.165 (0.054)
Participation rate, private-sector wage subsidy	0.021 (0.009)	0.020 (0.008)	0.021 (0.009)
Regional characteristics at the NUTS-3-level			
Population density (inhabitants per m^2), 2001	1,426.418 (1,628.337)	1,257.246 (1,512.787)	1,427.548 (1,629.023)
Nr. of enterprises, agriculture/forestry/fishing, 2011	798.314 (704.267)	866.649 (707.985)	797.858 (704.220)
Nr. of enterprises, manufacturing, 2011	265.084 (146.031)	293.923 (157.480)	264.892 (145.932)
Nr. of enterprises, construction, 2011	359.127 (149.531)	372.978 (163.316)	359.035 (149.430)
Nr. of enterprises, wholesale/retail trade, etc., 2011	925.160 (469.656)	981.546 (497.059)	924.784 (469.446)
Nr. of enterprises, transportation/storage, 2011	170.740 (96.500)	174.058 (102.850)	170.718 (96.456)
Nr. of enterprises, accomm./food service activities, 2011	429.342 (259.340)	427.251 (245.320)	429.356 (259.431)
Nr. of enterprises, information/communication, 2011	261.948 (179.401)	273.405 (197.608)	261.871 (179.271)
Nr. of enterprises, financial/insurance activities, 2011	140.917 (74.708)	151.821 (81.944)	140.844 (74.652)
Nr. of enterprises, real estate activities, 2011	370.427 (225.223)	393.387 (255.820)	370.273 (224.997)
Nr. of enterprises, prof./scientif./techn. act., 2011	996.828 (639.145)	1056.261 (708.612)	996.431 (638.638)
Nr. of enterprises, admin./supportive service act., 2011	198.384 (110.880)	202.557 (115.648)	198.356 (110.847)
Nr. of enterprises, education, 2011	131.491 (94.244)	139.618 (109.168)	131.437 (94.134)
Nr. of enterprises, human health/social work, 2011	486.956 (299.606)	534.989 (333.311)	486.635 (299.342)
Nr. of enterprises, arts/entertainment/recreation, 2011	198.023 (125.120)	196.509 (129.658)	198.033 (125.089)
Nr. of enterprises, other service activities, 2011	481.096 (236.471)	513.687 (267.124)	480.879 (236.238)
N	658,341	4,367	653,974

Sources: ASSD and PES data. Notes: All values displayed are means. Standard errors in parentheses.

Notes

[1]In the evaluation sample, mean program duration was about 7 months in 2008, 205 days for men and 215 days for women.

[2]Geographic coordinates of projects and unemployed individuals are obtained using the Stata module geocode3 that retrieves coordinates via the Google Geocoding API (V3). Travel times and distances by car are computed with the Stata module traveltime3 which retrieves this information via the Google Distance Matrix API (V3). Euclidean distances are computed via the Stata module globdist, based on the geocodes.

[3]The coefficient is 0.697, indicating that, other factors being fixed, one more population-group-specific program place per person increases individual treatment probability by 69.5 percentage points.