Reframing Active Labor Market Policy: Field Experiments on Barriers to Program Participation

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Abstract

Governments struggle to attract unemployed workers to their widely offered job training programs. In three randomized field experiments with 50,000 job seekers, we investigate the potential of informational interventions to encourage participation in job training programs. Raising awareness about the availability of job training increased program enrollment by 18%. Signaling program cost with a voucher to reduce internalized stigma increased completion by 28%. Effects were sizable and concentrated among women and low-income job seekers. Notably, job training did not result in higher employment or wages. These findings indicate that while low-cost informational interventions effectively boost participation, the overall success of job training programs in enhancing employment prospects hinges on their fundamental design.

Keywords: job training, program participation, information friction, social stigma, field experiment
JEL codes: J64, J68, C93, D04, D83

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1 Introduction

"No one cares if a course fits your profile or not. The main focus is that you are no longer adding to the unemployed numbers."

– Job seeker in our survey, Austria (2021).

"I am not a blip on a computer screen or a national insurance number, I am a man."

– Job seeker in the Ken Loach's movie "I, Daniel Blake" (2016).

Modern welfare states provide comprehensive social support to disadvantaged people including to unemployed workers. However, take-up of benefits, public services, and social programs by eligible populations is incomplete (UN Special Rapporteur, 2022). Following one explanation, targeted groups are simply not aware of their eligibility and face administrative burdens in accessing their benefits and services (Altmann et al., 2018; Barr and Turner, 2018; Belot et al., 2019; Haaland et al., 2023). However, even if they know about the programs, psychological frictions prevent eligible groups from accessing their entitlements (Bhargava and Manoli, 2015; Finkelstein and Notowidigdo, 2019; Goldin et al., 2022; Linos et al., 2022a). Such reasons are particularly likely for unemployed people, who are often seen as failing to contribute, which encourages blame, results in shame and social stigma related to reliance on the welfare state (Goffman, 1963; Moffitt, 1983; Walker, 2014). It raises the question whether individuals eligible for social programs are simply not aware of their eligibility, or whether psychological frictions associated with shame and stigma prevent them from accessing benefits, services and programs provided to them including training for job seekers.

As a main pillar of active labor market policies (ALMP), public employment services (PES) provide training to job seekers to improve their re-employment prospects. While governments spend large sums of public budgets on these programs, many job seekers are hesitant to participate.[1] Information frictions from a lack of awareness and psychological frictions from social stigma attached to public training programs constitute potential barriers faced by job seekers to engage in training (Heckman and Smith, 2004) that recently received renewed attention (Dhia and Mbih, 2020; Leduc and Tojerow, 2023; Muller et al., 2023). By contrast, preferences not to participate in training-even if offered at no cost-constitute an alternative explanation for low training enrollment. The distinction between barriers and preferences is important in guiding policy makers to understand whether to support individuals access' to social programs or respect their individual choices (Bergman et al., 2022).

[1] Governments spend on average 0.5% of GDP across OECD countries with up to 2% in European countries with the most developed active labor market programs (OECD, 2023). On average, less than 1% of the labor force participates annually in job training programs.

We investigate potential barriers for job seekers' hesitancy of engaging in training including the role of information frictions and psychological frictions. We test three ways to overcome these barriers and increase training including raising awareness about training programs, signaling the monetary value of job training to reduce internalized stigma, and providing information on what jobs employers are looking to fill. We further evaluate whether training has the intentioned effect of improving re-employment and wages. We do this by running three pre-registered field experiments at scale in collaboration with the PES involving 50,000 unemployed workers. The current version of this paper reports the outcomes of the first experiment with 11,000 job seekers.

Active labor market policies are intentioned to support job seekers to find re-employment but PES caseworkers in several countries struggle to fill program spaces due to low demand. Training programs for unemployed workers are a subset of ALMPs and are among the most evaluated policies in the world (Card et al., 2010). On average, they are found to generate modest positive effects on re-employment and wages over the long run but are characterized by large underlying heterogeneity between programs and types of workers. Positive effects are more pronounced for disadvantaged groups in the labor market including women (Card et al., 2018). Job seekers can choose among a wide variety of training programs as long as their choices are deemed reasonable by the PES. However, caseworkers struggle to fill their training programs with unemployed job seekers being hesitant to participate. This is puzzling given that training programs are provided at no financial cost to job seekers. Why are unemployed workers hesitant to participate in training programs as their "free lunch"? Answering this question sheds light on how to overcome barriers to increase training to improve human capital and skills in the labor force. Further, it helps to understand whether and under what conditions training helps job seekers to get re-employed. In a broader context, it adds to the understanding of possible barriers that prevent disadvantaged groups from accessing public services resulting in non-take-up.

A straightforward explanation is a lack of awareness of unemployed job seekers who simply may not know about the training programs available to them due to information frictions. Once job seekers are fully aware of the programs provided to them, social stigma of such programs may cause psychological frictions that prevent participation. However, barriers including from informational or psychological frictions are not the only possible reason to prevent job seekers from training. An alternative set of explanations rests around individuals' preferences. Individuals may anticipate that training will not help them and they may be better of spending their time following other job search strategies or have other personal constraints, or simply enjoy leisure. Disentangling barriers from preferences is important to understand whether policy makers should aim at reducing barriers.

Intervention We answer this question with a set of three multi-armed field experiments at scale with 50,000 job seekers. The current version of this paper reports the findings of the first of three experiments. It includes three treatment arms with information treatment provided to unemployed workers. The intervention was implemented in the first quarter of 2021 by the PES of Lower Austria (*Arbeitsmarktservice Niederösterreich (AMS NÖ)*). The goal was to increase enrollment in training with the aim of increasing re-employment of job seekers.

We randomly allocate 11,000 unemployed job seekers in Lower Austria to three treatment groups and one control group using stratified randomization. The first treatment group receives an e-mail with information on training programs offered by the PES; the second treatment group additionally receives a training voucher to be redeemed with the PES up to a value of €15,000; the third treatment group additionally receives information on which occupations have the most open vacancies. The intervention consists only of the variation in the information provided with all options and obligations kept constant for individuals of all four groups. The treatments are stacked and designed to separate out interacted effects of raising awareness (treatment 1), combined with signalling the training program's monetary value (treatment 2), and combined with providing information on the labor market (treatment 3). We observe demographic-, benefit- and job characteristics from administrative records and link them to our survey data.

Main findings Our main empirical findings can be divided in three areas: training, employment, and inequality among unemployed workers. For average **training outcomes**, three sets of findings are noteworthy. First, **raising awareness** has a large positive effect on training enrollment while **signaling the monetary value** on top helps to improve program completion. The magnitude of an 18%-21% increase in training enrollment compared to baseline is striking given that the intervention consists only of one e-mail. The effect on training completion is even stronger indicating a positive effect on completion even among always takers. This implies that unemployed workers who would have participated in training without the intervention are more likely to complete training programs due to the intervention. Signalling the monetary value of job training—highly stigmatized programs— increases program completion beyond its increase in participation. The increase in program completion amounts to 28% compared to baseline, and compares to an 19% increase for raising awareness.

Second, the increase in training is not even across programs and results in **spillovers** on other active labor market programs. The increase in job training is driven by a relative shift towards more ambitious programs. Both, the e-mail and voucher increase enrollment in programs with longer duration, typically oriented toward learning job-related skills and human capital formation. Both treatments also increase participation in examined programs, which are more ambitious and provide a certificate for successful completion. Signalling the monetary value leads to a larger increase in completion of ambitious programs beyond the increase in participation. Spillovers on other active labor market programs are not negligible. The increase in training is driven in part by a substitution of enrollment in other ALMPs, in particular application course enrollment and subsidized employment. Enrollment in application courses decreases by about half of the increase in training program enrollment. Subsidized employment also shows signs of a decline. Raising awareness, thus, spurs substitution of job-search and hiring subsidies with training programs.

The average results are driven by substantial **heterogeneity** across sub-groups. Effects are concentrated among disadvantaged groups: women and job seekers with lower income. Both groups are more likely to enroll in training programs at baseline, and drive the training increase by a strong response to the information intervention.

Third, reducing information frictions on labor markets can have **unintended consequences**. Informing job seekers which occupations have the highest numbers of open job vacancies results in null effects cancelling out any positive effects from raising awareness and signaling the monetary value of training programs (e-mail + voucher + information, treatment 3). Those occupations with a the highest number of open vacancies are viewed as unattractive, in particular to job seekers with better prospects as the heterogeneity analysis and surveys reveal.

Turning to average **employment outcomes**, we find no positive effects of training programs on labor market outcomes. Using intention-to-treat (ITT) and instrumental variable (IV) estimation approaches, we find that training programs do not increase re-employment rates or wages of unemployed job seekers. The findings are robust to a number of variable definitions with no signs of meaningful heterogeneity across types of training programs or sub-groups of unemployed workers.

Implications The results demonstrate the potential of information in overcoming barriers for disadvantaged populations. Raising awareness to reduce information frictions (treatment 1: e-mail) and framing information to reduce psychological frictions (treatment 2: e-mail + voucher) increase training to foster human capital formation. Providing information does not always work in the same way. It can also have unintended consequences, such as discouraging unemployed workers from training (treatment 3: e-mail + voucher + occupation info). Version 1 and 2 of the intervention are effective means to reducing barriers to social programs.

The results also reveal that government funded job training programs do not necessarily improve labor market prospects of unemployed workers. The absence of positive effects on employment or wages raises doubts about governments' intentions to nudge job seekers into widely offered training programs. Remaining hesitancy of job seekers' to enroll in job training may reflect actual preferences about how to allocate their time instead of barriers to access social programs.

Literature We study job training as an archetypical social program as Heckman and Smith (2004). Our study contributes to the literature on barriers to social program take-up (Moffitt, 1983; Bertrand et al., 2000; Currie et al., 2001; Dahl et al., 2014; Finkelstein and Notowidigdo, 2019; Anders and Rafkin, 2022). Recently, attention has shifted to studying the effect of messages on information and psychological frictions. Heckman and Smith (2004) suggested that the lack of awareness of program eligibility is a major determinant of job training program participation. **Information frictions** for unemployed workers and interventions to address them have been studied by a surging experimental literature as summarised by Haaland et al. (2023). A set of studies have provided information on job search in form of a simple brochure (Altmann et al., 2018) or more encompassing online job search tools (Belot et al., 2019; Briscese et al., 2020; Barbanchon Le et al., 2023), which resulted in modest positive employment effects. Focusing on training programs, Barr and Turner (2018) show for the U.S. that letters sent from the

PES informing job seekers about benefits and costs of training substantially increase training participation. Building on these field experiments around information frictions, Dhia and Mbih (2020) investigate the types of information that can foster training participation, by varying framing of e-mails sent by the PES in France. They find increased callback rates for job seekers who received information about returns to training and the simplicity of the application process, but no differences in training participation. Leduc and Tojerow (2023) randomly assign an e-mail with information on job training programs to job seekers similar to our treatment 1. Contrary to our positive results on training, they find only positive effects on intention to enroll in training but not on actual enrollment. Muller et al. (2023) evaluate the effects of information provision on labor demand for job seekers using an e-mail that contains suggestions about suitable alternative occupations similar to our treatment 3. Similar to us, they find no impact on received benefits and earnings but they find increases in occupational mobility. Our study further contributes by combining three factors in one field experiment with three treatment arms that allow us to separate the interacted effects from adressing information frictions from a lack of awareness of training (treatment arm 1), psychological frictions from stigma associated with training programs (treatment arm 2), and information frictions on labor demand (treatment arm 3). In addition, we are able to uncover the mechanisms for job training assignment by tracing the steps in job training assignment from job seekers' intention to train, the role of caseworkers, training enrollment and completion-for the first time in a quantitative study.

To date, the role of **psychological frictions** related to non-take-up of active labor market programs remains unexplored, which we investigate. Evidence from the lab points to an important role of social stigma for non-take-up of benefits (Friedrichsen et al., 2018). A recent field experiment in Egypt finds non-stigmatizing information to modestly increase take up in job search assistance with large heterogeneity (Osman and Speer, 2023). Previous studies have focused on other social policies, such as Temporary Aid to Needy Families (TANF), food stamps, or unemployment insurance. However, these policies are entitlement programs, where participation depends primarily on the decisions of potential participants to apply. By contrast, participation in job training differs as it depends on the choices of both potential participants and street-level bureaucrats (Zweimüller and Winter-Ebmer, 1996; Heckman and Smith, 2004). Evidence from entitlement programs point in divergent directions concerning the importance of information frictions versus psychological frictions. A number of field experiments carried out in the context of tax filing in the U.S. include social benefit applications, such as the EITC. These studies find that even well designed behaviorally informed low-touch outreach efforts cannot overcome the barriers faced by low-income households. Bhargava and Manoli (2015) find that mere provision of information to raise awareness via a mailing can increase take-up of EITC, while framing interventions to overcome psychological frictions by reducing stigma did not have an added benefit. Simple mailings to share information on free tax preparation increase benefit take-up (Goldin et al., 2022). By contrast, changing the framing of messages to overcome psychological frictions does not have any effect on claiming social benefits (Linos et al., 2022a). Framing of messages to overcome psychological frictions does matter in other contexts including on housing code compliance (Linos et al., 2020), university scholarship registration and college enrollment (Linos et al., 2022b), and emergency rental assistance (Lasky-Fink and Linos, 2022). Experimental studies in Europe are less common. Text messages are found to have no impact on public services usage by young people in France (Hervelin, 2021). Our study documents the potential of framing access to job training-widely offered social programs-to reduce non-take up.

Barriers versus preferences Both sets of explanations, information frictions and psychological frictions, can be subsumed as barriers to access welfare services. A third set of possible explanations arise around individuals' preferences. Some people eligible for social programs may prefer not to participate if the programs offered are not helpful to them in finding a job. In this case, the opportunity cost of their time is too high as other job search strategies are more effective. Some individuals may also prefer to stay out of employment. Following Bergman et al. (2022), barriers preventing eligible populations from taking up social programs should be identified and consequently removed to expand access and increase effectiveness of social policies. By contrast, preferences of eligible populations should be respected to maintain their agency without imposing paternalistic social policies that may result in unintended consequences. Our study investigates the role of potential barriers to training.

Out study focuses on the subset of training programs for job seekers, which are part of **active labor market policies**. They are among the most evaluated policies worldwide. Their evaluations have substantially contributed to the development of modern methods for causal inference. Training programs for job seekers are found to have overall modest positive effects on re-employment and wages as summarized by the meta-analyses by Card et al. (2010, 2018) as well as by extensive reviews (Heckman et al., 1999; Kluve, 2010; Crépon and van den Berg, 2016). However, large differences between program types, context and across sub-groups exist.

Unintended consequences of active labor market policies have thus far received less attention. Black et al. (2003) observe an increase in unemployment insurance exits driven by a threat effect from assignment of job seekers to mandatory training and job-search programs. Crépon et al. (2013) carry out a large-scale clustered randomized controlled trial in France and find large displacement effects of job assistance programs. Similar unintended displacement effects are found in an observational study for Denmark (Gautier et al., 2018). Our findings contribute to uncovering unintended consequences of labor market policies by documenting non-existent re-employment effects of training programs.

Unintended consequences may be understood by connecting labor market evaluations with insights from behavioral theory that shape our understanding of job search. Bandiera et al. (2021) find that vocational training as a standalone program achieves better labor market outcomes than in combination with job-search assistance. **Discouragement** emerges as the main mechanism behind the surprising result: lower than expected call-back rates lead to negative effects of job-search assistance. While their study is focused on youth employment in Uganda, our study in the context of a high-income country with one of the most developed PES, finds similar results driven by discouragement of job seekers of all age groups when learning about existing labor demand (treatment arm 3). This is in line with Spinnewijn (2015) and the burgeoning literature on duration dependence that has documented job seekers overoptimism about their employment prospects (Mueller et al., 2021; Maibom et al., 2023; Abebe et al., 2021; Miano, 2023; Adams-Prassl et al., 2023). Job seekers overoptimism has also been documented for Austria (Böheim et al., 2011). In contrast to this literature, which largely finds positive employment effects of correcting misbeliefs, we document negative consequences for job seekers' training and null effects on re-employment. Medium and high skilled workers get discouraged when learning about occupational labor demand.

The **heterogeneous effects** of our study for take-up in active labor market programs document a "Matthew Effect". Groups with higher training enrollment at baseline disproportionally increase their training due to the intervention. This may be the result of "access bias" (Bonoli and Liechti, 2018) from training programs disproportionally targeting disadvantaged groups, such as unemployed women who return to the labor force after childbirth. Information interventions in other contexts find that heterogeneity in responses is driven disproportionately by disadvantaged groups especially by income (Heffetz et al., 2022; Lasky-Fink and Linos, 2022) and education (Barbanchon Le et al., 2023), which corresponds to our results. While we do not find significant employment effects for any group, we find suggestive evidence that disadvantaged job seekers are more likely to benefit from training. Indeed, training programs are found to be particularly effective when targeting low-wage workers (Katz et al., 2022) and short-term unemployed people (Baird et al., 2022). Disadvantaged job seekers typically benefit disproportionally as information experiments on job search have shown (Altmann et al., 2018; Belot et al., 2019). Liechti et al. (2017) uncover a potential mechanism for this heterogeneity in their correspondence experiment: recruiters evaluate candidates more distant from the labor market better if they have participated in an active labor market program, while for stronger candidates, participation results in stigma and worsens the assessment.

Roadmap The rest of this paper is structured as follows. Section 2 provides an overview of active labor market policies and the context of the study. Section 3, building on our pre-analysis plan, details our experimental design and analysis. Section 4 presents our empirical results for training intentions, training, and employment. Section 5 investigates mechanisms behind the treatment effects. Section 6 discusses the results and Section 7 concludes.

Appendix A presents additional details on the design and Appendix B additional results of intervention 1. Appendix C provides details on the complementary survey including the questionnaire and additional results. Appendix D reports the design and results of intervention 2.

2 Background

This section provides an overview of the objectives, history and types of of active labor market policies. It also discusses training programs in the Austrian context, and their assignment and eligibility criteria. Lastly the impact of the Covid pandemic on the labor market is reviewed.

Objectives Active labor market policy has an economic policy and a social policy function with its dual objective of raising efficiency in labor markets while promoting equity among unemployed workers. Efficiency concerns have primarily centred around raising employment, improving job-worker matching, and increasing human capital, while equity concerns aim at levelling the risk distribution between unemployed job seekers and providing employment opportunities for disadvantaged groups. (Clasen et al., 2016; Boeri and van Ours, 2021; Lehner and Tamesberger, ming). Thereby, ALMPs complement passive labor market policies such as unemployment benefits and early retirement schemes (Ebbinghaus, 2020).

History of ALMP Active labor market policy has a long history but public works projects existed even before and were implemented at scale already during the 1920s in post-WWI Europe and during the 1930s Great Depression under the New Deal in the US (Vlandas, 2013). Sweden pioneered modern ALMP manpower programs in the 1950s in its notorious "Rehn-Meidner plan" combining expansive macroeconomic policies with ALMPs with the objective of facilitating rapid labor reallocation and up-scaling to raise productivity while sustaining full employment (Weishaupt, 2011). Following the Nordic examples, Austria was in the late 1960s one of the first countries to introduce far reaching training programs for unemployed workers (Hofer et al., 2013). The sustained increase in unemployment during the 1980s and 1990s resulted in a large up-scaling and convergence of ALMPs across high-income countries (Clasen and Clegg, 2011). Under the "activation" turn in the 1990s (see OECD (1994) for the landmark study at the time), PES introduced increasingly strict benefit conditionality that oblige job seekers to participate in ALMPs once assigned to be eligible for benefits (Bonoli, 2010; Knotz, 2020). Since the 2008 Great Recession, ALMPs continuously expanded the range of programs (OECD, 2018; Boeri and van Ours, 2021) with increasing convergence of activation requirements across high-income countries (Immervoll and Knotz, 2018).

ALMP types Programs can be divided into at least four categories: Job-search assistance (activation), training, employment subsidies, and public employment creation (Card et al., 2018). [2] Job-search assistance includes one-on-one counseling as well as courses in which job seekers learn job-search skills and apply for jobs. These typically focus on job search strategies and CV preparation. Training refers to programs focused on sustaining, deepening, and acquiring skills to build human capital, facilitate re-employment and spur occupational mobility. Employment subsidies incorporate hiring subsidies for employers as well as a smaller subset of funding support to job seekers who found a start up business. Public employment is targeted at a specific group of unemployed workers, the most disadvantaged job seekers including those with long unemployment spells and health conditions (Kasy and Lehner, 2023). Our intervention is targeted at training programs but we are able to observe spillovers on other ALMP types.

[2] For alternative classifications see Vlandas (2013) and Ebbinghaus (2020).

Job training programs in Austria Training programs in Austria are recognized as among the most developed in the world and the Austrian PES has served as a role model for other countries. Expenditures for ALMP are among the highest as a share of GDP across high-income countries (OECD, 2023). Training programs constitute the largest pillar and receive 2/3 of the annual ALMP budget (Hofer et al., 2013). Training offered by the PES includes over 1,000 programs that cover advancing skills within an occupation as well as acquiring new skills to foster occupational mobility (Zweimüller and Winter-Ebmer, 1996; Eppel et al., 2022). Common programs include mechatronics, plumbing, ICT, programming, restaurant management, hotel and catering assistance, and nursing. Program duration varies from a few days up to 1.5 years with longer programs offering high quality training for job-specific skills. Among training program participants, about 40% graduate with a certificate after successfully passing an exam. Programs with exam constitute more ambitious programs. During training enrollment, individuals continue to receive the same amount as their unemployment benefits which is topped up with a small amount of €4 per day during our observation period to account for an increase in expenditures during training participation.

Assignment, eligibility and conditionality Caseworkers are street-level bureaucrats employed by the PES as job counselors with several responsibilities. They provide job-search assistance and monitor job-search effort. They administer benefits and decide on program assignment. Job seekers meet their caseworkers regularly for consultations, where they discuss about training opportunities besides benefits and job-search. The dual role of caseworkers reflects a deeper ideological divide about providing welfare support to unemployed workers versus demanding active job-search and work availability "in return".

Every unemployed job seeker is eligible to participate in training programs. While program participation comes at no financial cost to job seekers, attendance is mandatory and repeated no shows risk sanctions such as benefit cuts.

Unemployed workers can express interest for a large number of ALMPs but caseworkers have the last say for program assignment. Unlike application courses to which caseworkers occasionally assign job-seekers with the aim of "restoring work morale", assignment to training programs is intentioned to follow job seekers' interest. In practice, 87% of caseworkers in Austria report that they assign job seekers to training programs of their choice, while only 6% report "exercising pressure" when assigning training programs (Schönherr and Glaser, 2023). By contrast, application courses serve more frequently as a disciplining device with 20% of caseworkers reporting to "exercising pressure" for assignment. "Meeting their target" for program assignment is another motive for caseworkers, which is equal for application courses and training programs.

Covid pandemic The intervention took place in February 2021 as part of a broader PES campaign *Corona Joboffensive* to promote job training programs. The intention was to prepare job seekers for the recovery phase post-lockdown, given the low likelihood of immediate re-employment during the lockdown period. This lockdown extended from November 2020 to May 2021, with temporary easing occurring between February and March 2021. The PES received additional funding and increase training capacity massively from February 2021, which led to a virtually unlimited supply of training programs only constraint by the demand of job seekers (Leitner and Tverdostup, 2023). The majority of training programs took place in person with safety measures in place while some programs moved online. The type of training programs offered was not affected by the pandemic.

3 Study design

We design a field experiment at scale (Harrison and List, 2004) to test whether information provision increases training and employment of job seekers. Job seekers receive an e-mail from the PES with varying content by treatment group to inform them about training opportunities. In this section, we provide an overview of the data and sample selection in Section 3.1, experimental design in Section 3.2, identifying assumptions in Section 3.3, and our approach to estimation and inference in Section 3.4. Tables and figures to describe our sample and treatment assignment are shown in Appendix A.

Further details on the study design are documented in the pre-registered pre-analysis plan (AEARCTR-0007141).[3] The experiment was approved by the Departmental Research Ethics Committee at the University of Oxford and by the Competence Center for Experimental Research at the Vienna University of Economics and Business.

3.1 Data

Administrative records We leverage a wide range of demographic-, benefit- and job characteristics from administrative data including (i) the PES internal registry for administrative data on unemployed workers (AMS Data Warehouse); and (ii) the "occupational-career monitoring" (Erwerbskarrierenmonitoring, EWKM), accessed via the AMS internal registry for social security registry data. Due to our reliance on administrative data, we face virtually zero attrition.

Surveys Additionally, we survey participants and link the data with the administrative records at the individual level. We collect detailed data on training intentions, experiences and perceptions, interactions with caseworkers as well as job search behavior and reservation wages. The surveys are distributed via e-mail to all individuals in our sample. We send the e-mails as researchers, ensure respondents anonymity, and communicate our independence from the PES. We design the questionnaire using Qualtrics following Stantcheva (2023). Section C.1 provides an overview of our survey questionnaire.[4] We achieve a response rate of 30%, which is relatively high compared

[3]The code implementing the study design was uploaded prior to the implementation of the intervention to GitHub at https://github.com/lukaslehner/Vouchers.

[4]The full questionnaire was pre-registered on the AEA RCT Registry at https://www.socialscienceregistry.org/versions/87136/docs/version/file.

to related studies (Dhia and Mbih, 2020; Leduc and Tojerow, 2023; Muller et al., 2023).

Sample With the pandemic, the composition of job seekers in Lower Austria has overall become more similar to the rest of Austria (table A1). Before the pandemic, a higher share of job seekers had a health restrictions, Austrian citizenship and lower educational attainment (columns (1)-(3)). In the rest of Austria, job seekers are on average younger, lower educated and hold less often Austrian citizenship or have a health restrictions (column (4)).

The sample of our first experiment includes the population of unemployed workers in Lower Austria with an unemployment spell of 2 to 3 and 6 to 12 months at the time of treatment.[5] Unemployed job seekers who are already enrolled in a training program or have a job offer accepted at the time of the intervention are excluded from the sample. The sample is further restricted to people who are at least 25 years old.[6]

This leaves us with 11,050 unemployed people (Table A1 column (3)). [7]. Among them, 52% are women, 30% are younger than 35 years and about 32% older than 50 years. 1/3 has no more than compulsory schooling. Just over 1/5 has a foreign nationality and an equally large share has a health restriction preventing them from working in certain occupations. 14.5% speaks only limited or no German.

3.2 Experimental design

Treatment assignment Three different treatment arms vary the type of information on training programs provided to unemployed job seekers. The PES informs participants about training programs in a natural context, i.e., without participants' knowledge about the experimental character. By contrast, participants in an artefactual context are ex-ante informed about the experiment, which may induce bias by affecting their beliefs or behavior (List, 2022). The unemployed people in the sample are randomly allocated to one of the three treatment groups or the control group.

We assigned study participants to one of three treatments and one control group using stratified randomization. We used the following covariates to construct the strata: gender, age, education (i.e., more than the legally required minimum), region, and unemployment duration. We constructed these variables from raw data for job seekers using the PES internal registry and the social secruity administrative data described above. All of these variables were used as available to the PES in February 2021.

For the stratified randomization, we first divided individuals into strata based on the variables described above. We constructed 145 strata for every possible combination of the values of the 5 strata variables ranging from 10 to 270 individuals per stratum as shown in Figure A1. We

[5] All unemployed workers with a spell of 3 to 6 months received the information treatment 1 without control group two weeks prior to the experimental intervention and were thus excluded from the sample.

[6] The PES runs specific programs for younger job seekers.

[7] The sample for the analysis is reduced to 10,714 since observations with missing values are excluded. Missing values include mainly citizenship and occupation as well as in few instances education and pre-unemployment income.

then assigned individuals randomly within the strata to one of the three treatment groups or the control group. The randomization procedure resulted in four equally-sized, balanced groups as shown in Appendix A.3. The pre-analysis plan contains further details on the treatment assignment(AEARCTR-0007141) (Lehner and Schwarz, 2021).

Intervention The intervention is based on an encouragement design. Job seekers receive an e-mail from the PES with varying content on job training. The treatments are stacked on top of each other, i.e., treatment group 2 receives the same e-mail as treatment 1 complemented with a voucher; treatment group 3 receives the e-mail and voucher of groups 1 and 2 complemented with information on occupations with open vacancies. The control group is not contacted but continues to have access to training and regular PES consultations. The formal training assignment mechanism remains the same for individuals of all four groups. The intervention was implemented in February 2021.

Treatment group 1 receives an e-mail with information on PES-provided training programs as shown in Figure A2. The intention is to raise job seekers' awareness of training programs to overcome information frictions that prevent them from participation.

Treatment group 2 includes a voucher for job training programs added to the e-mail as shown in Figure A3.[8] Although, training program enrollment is costless to job seekers irrespective of which treatment group they are assigned to, the voucher indicates a value of €15,000.[9] The value was chosen as an upper bound for training program costs as it corresponds to the cost incurred to the PES by their most expensive training programs on offer. By signalling the monetary value of the programs, the treatment is intended to reduce internalized stigma of job seekers that create psychological frictions and prevent job seekers from program participation. The voucher is, thus, solely a way of framing access to training programs that are already available to job seekers.

Treatment group 3 receives a list of occupations with the highest number of open vacancies in addition to the e-mail and voucher as shown in Figure A4. Job seekers are found to search in occupations with relatively few vacancies (Sahin et al., 2014). This information is intended to encourage job seekers for training in occupations with high labor demand and broaden job search beyond their previous occupation. Previous studies have found that improved access to information can broaden their search and increase the number of job interviews (Belot et al., 2019).

E-mail clicks We collect data on whether an e-mail was received and opened, and on clicks on hyperlinks in the e-mail to assess whether the intervention was successfully implemented. Figure A5 shows a graphic of the e-mail and hyperlink clicks observed.

[8]The stacked design is necessary since providing a voucher to signal the monetary value inherently raises awareness as well. While we cannot rule out interaction effects between the treatments, the stacked design allows us to keep the effect of raising awareness about training programs constant across the treatment groups to separate out the interacted effect of signaling the monetary value.

[9]The voucher also includes €3.000,- for any training not provided via the PES.

3.3 Identifying assumptions

Training outcomes Assignment to treatment and control groups is based on stratified randomization. Due to the clean randomization of participants into control and treatment groups, it is possible to compare the relevant outcome variables directly between the 4 groups. This provides us with an unbiased estimate of the treatment effect that does not hinge on any assumptions other than the random assignment into the groups. The results for training can thus be interpreted as intention-to-treat (ITT) generalizable to the entire population of unemployed job seekers in our sample (Imbens and Angrist, 1994).

With the additional assumption that all effects are mediated by opening the e-mail, these estimates can be scaled up by the effect of treatment on the probability of opening the e-mail, which yields instrumental variable estimates of the local average treatment effect (LATE) of having received the information treatment. The effect of assignment on opening the e-mail is estimated to be around .91, so that the corresponding instrumental variable estimates of all treatment effects on training enrollment would be about 10% higher of the reported ITT effects.

Employment outcomes We rely on the same ITT approach to estimate employment outcomes and additionally use an instrumental variable (IV) approach. Training is driven by those job seekers who enroll into training programs because of the treatment. While this is a small share of 2 percentage points who are shifted at the margin, we report our baseline estimations as ITT, which are generalizable to the entire population.

For the IV approach, we use the information intervention to instrument training. This gives us the LATE, which is representative for compliers, i.e., those job seekers at the margin of enrolling into training (Angrist et al., 1996). Our instrument, the information intervention, is correlated with the endogenous variable, training. Our IV estimation has an F statistic above 10, which is conventionally used as a threshold to qualify strong instruments. We know that our instrument is as good as random since we randomly assigned it. Our identification rests on the exclusion restriction: our instrument affects the dependent variable, employment outcomes, only through training. In other words, the information intervention itself does not affect employment.

3.4 Estimation and inference

First, we compare the simple means between the treatment and control groups. To increase precision, we estimate parametric regressions for the treatment effects using the following estimation regression:

$$Y_i = \beta_0 + \beta_1 T_1 + \beta_2 T_2 + \beta_3 T_3 + \mathbf{X_i} + s_i + \epsilon_i \tag{1}$$

where Y_i refers to the outcome variables for individual i. Depending on the scale of the outcome variable, an OLS (continuous) or a Logit (binary) regression is used. Our outcome variables are measured at different time periods and for each time period a separate regression is estimated to measure time-varying treatment effects. T_1 to T_3 refer to the treatment groups as described above. Further, as we used stratified randomization, we include strata dummies, following Athey and Imbens (2017). We additionally control for all socio-demographic variables as recorded before treatment $\mathbf{X_i}$ that were not used for stratification.

For employment outcomes, we maximize statistical power by pooling individuals in the treatment groups that increased training (treatment groups 1 and 2). Table B11 presents the employment results for the three treatment groups separately for robustness.

The heterogeneity analysis is conducted via subgroup regressions of the equation above for the variables specified in the pre-analysis plan.

4 Results

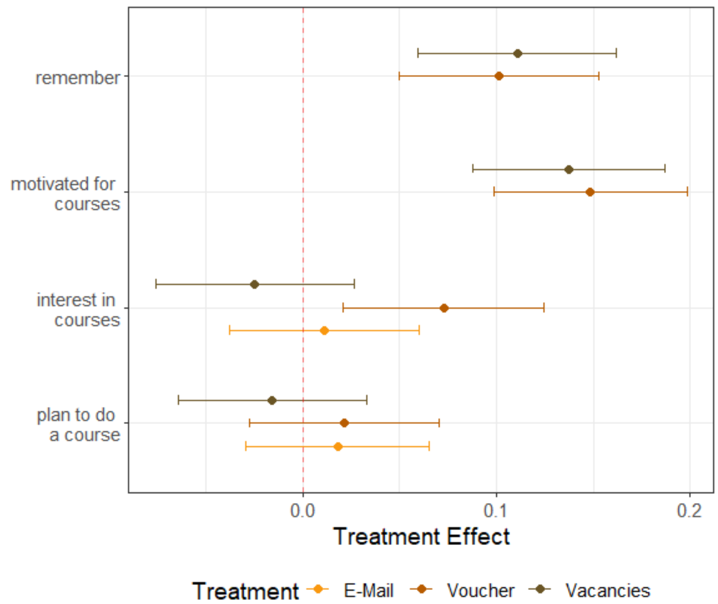
Our results are structured around three groups of outcomes: training intentions in Section 4.1, training behavior in Section 4.2, and employment in Section 4.3. Figures 1-4 and tables 1-3 present our main results. Additional figures with results for robustness using alternative estimation approaches and variable definitions, timing patterns, and heterogeneity are documented in Appendix B.

4.1 Training intentions

The first outcome to assess the treatments' effectiveness is to examine whether they shifted intentions to train by job seekers. We measure intentions with the survey described in Section 3 and Section C.1. We compare interest and plans for course participation between the treatment and control groups (Figure 1). We also compare whether the type of treatment affected respondents memory of the treatment and motivation for courses.

Findings Vouchers raise job training intentions (Figure 1). General interest in courses offered by the PES increases after receiving the voucher. Interest and plans for courses seems to decrease for recipients of the vacancies treatment though not statistically significant. Among those who were treated, recipients of the voucher and vacancies information were more likely to remember the information received. Voucher and vacancies information recipients showed also higher motivation for courses compared to those who only received the e-mail. Overall, these results demonstrate that the treatments were successful in shifting job seekers intentions to engage in training.

Figure 1: Averate treatment effect on intentions to train



Note: Confidence intervals are reported at the 90%-level.

4.2 Training behavior

We now assess whether the treatments affected job seekers actual training behavior. First, we present baseline results on training before proceeding to timing patterns and sub-group results. We measure training by enrollment and completion of training programs. The primary intention of the intervention is to encourage unemployed workers to participate in training, which is why we look at enrollment as our main outcome. While program completion is generally desirable, one reason for dropping out of training programs is by finding a job. Table 1 reports the results of the 3 treatment arms on training 12 months after the intervention. The estimates control linearly for baseline covariates to increase precision.

At baseline, 11% of job seekers enroll in a training program within 12 months after the intervention (Table 1, column 1). Among all the programs, 8% last for 6 months or longer up to a maximum of 18 months (column 3). Longer programs have a stronger focus on equipping job seekers with new skills and human capital formation, while shorter programs often focus on refreshing existing knowledge or adding complementary skills. Close to 5% of job seekers participate in training programs that complete with an exam, which is another indicator for more ambitious training programs (column 4). Besides training, the PES provides a range of active labor market programs discussed in Section 2. We present results for enrollment in application courses and subsidized employment to account for spillover effects on other ALMPs.[10] At baseline,

[10] Public employment programs are targeted at a different sub-group: the most disadvantaged job seekers with very long unemployment spells and health conditions.

4.5% of job seekers participate in application courses (column 5), while 1 in 4 job seekers finds a job supported by employment subsidies (column 6) within 12 months of starting their unemployment spell.

Findings The e-mail and voucher treatments both lead to a significant increase in training enrollment. The increase is substantial in magnitude with 18% and 21% from baseline (Table 1 column 1), which results in around 13% of treated job seekers participating in training compared to 11% of untreated job seekers (Figure 2). The increase lasts over time with no catch up over the first year since the intervention (Figure B1). The effect size for treatment group 2 (voucher + email) is slightly larger than for treatment group 1 (e-mail) but the difference in the effect sizes is not statistically significant.

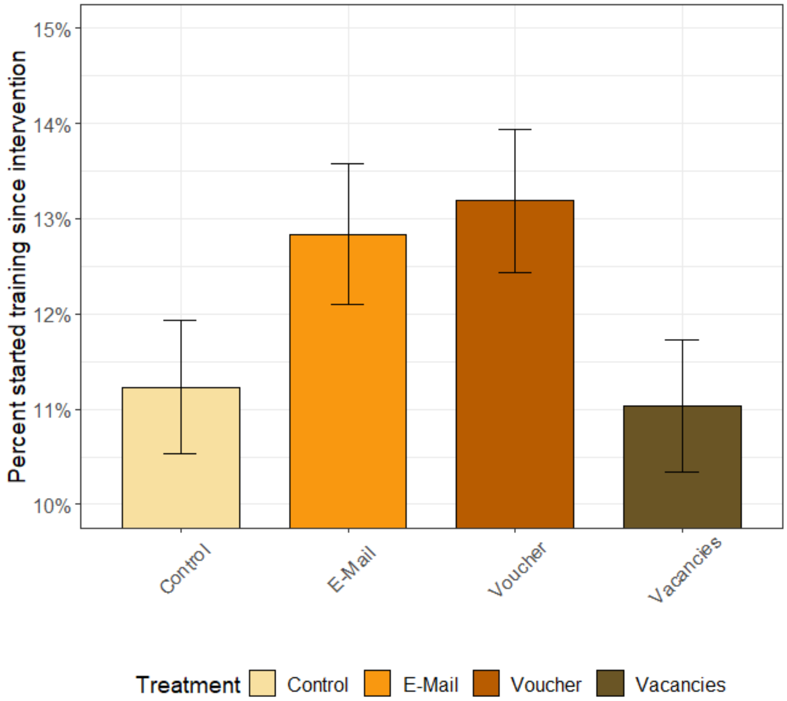
The information on vacancies, by contrast, does not increase training. For the interpretation, it is important to keep in mind that the information on vacancies is added to the e-mail and voucher as provided to treatment groups 1 and 2. We can interpret the null effect of treatment group 3, thus, as the vacancy information having a negative effect on aggregate training, which offsets the gains from treatment 1 and 2 in magnitude.

The e-mail and the voucher treatments both increase completion of training programs (column 2). The increase in completion is lager than for participation, particularly for the voucher with 28%. The treatments, thus, increased the share of training programs that were completed-even for job seekers who would have enrolled in training programs regardless of the intervention ("always-takers").

The treatments also tend to affect the type of training undertaken. Job seekers shift participation to more ambitious training programs defined as longer in duration (column 3) and courses with an examination on completion (column 4).

The increase in training for the e-mail and voucher treatments has a spillover effect on enrollment in other active labor market programs. Around half of the increase in training of job seekers who receive the e-mail can be attributed to a decline in application course enrollment (column 5). This equals a 20% drop in application course enrollment. Job seekers who receive the voucher tend to take-up less subsidized employment, which equals the magnitude of the increase in training enrollment (column 6). These results underscore that the increase in training is largely driven by job seekers substituting other active labor market programs with training.

Figure 2: Training enrollment



Note: Confidence intervals are reported at the 90%-level.

Table 1: Average treatment effects on active labor market programs

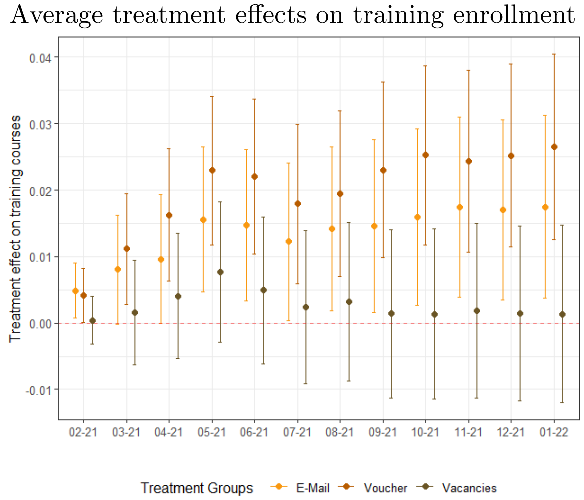
	Dependent variable:					
	Training	Training completion	Long training	Examined training	Application courses	Subsidized employment
	(1)	(2)	(3)	(4)	(5)	(6)
E-mail	0.020**	0.018**	0.015**	0.011*	−0.009*	−0.005
	(0.008)	(0.008)	(0.007)	(0.006)	(0.005)	(0.012)
Voucher	0.024***	0.026***	0.014**	0.008	−0.007	−0.019
	(0.008)	(0.008)	(0.007)	(0.006)	(0.005)	(0.012)
Vacancies	0.0005	0.006	−0.003	0.003	−0.005	−0.019
	(0.008)	(0.008)	(0.007)	(0.005)	(0.005)	(0.012)
Control Mean	0.112	0.094	0.078	0.047	0.045	0.257
Control SD	0.316	0.292	0.268	0.211	0.208	0.437
Observations	10,714	10,714	10,714	10,714	10,714	10,714

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Timing patterns To analyze timing patterns in the treatment effects of active labor market programs as suggested by Card et al. (2018), we investigate the temporal dimension of treatment effects on a monthly basis for 12 months following the treatment. Regarding outcomes, we consider whether job seekers participate in a training program since the treatment took place. Figure 3 shows the treatment effect on training program enrollment per month and Figure B1 cumulatively. Figure B2 shows the substitution of application courses and Figure B3 shows the substitution of subsidized employment per month.

The increase in training enrollment for treatment and control groups is steep in the first 4 months after the intervention and flattens over time as an increasing share of job seekers start training or change their employment status (Figure 3). Within the first 4 months, the voucher treatment increases training enrollment by around 2.5% and the newsletter by around 1.5% compared to the control group. The treatment effect plateaus afterwards as many job seekers who started training remain enrolled in their programs. The positive treatment effects on training enrollment are sustained over time with no catch up effect of the control group for the first 12 months after treatment (Figure B1). The job info shows no signs of a significant or substantial increase in training enrollment. The reduction in application course enrollment starts right after the intervention, reaches its strongest magnitude about 4 months after the intervention, and remains constant thereafter (Figure B2). Reductions in subsidized employment start to emerge only about 5 months after the intervention and intensify over time (Figure B3).

Figure 3: Average treatment effects on training enrollment over time



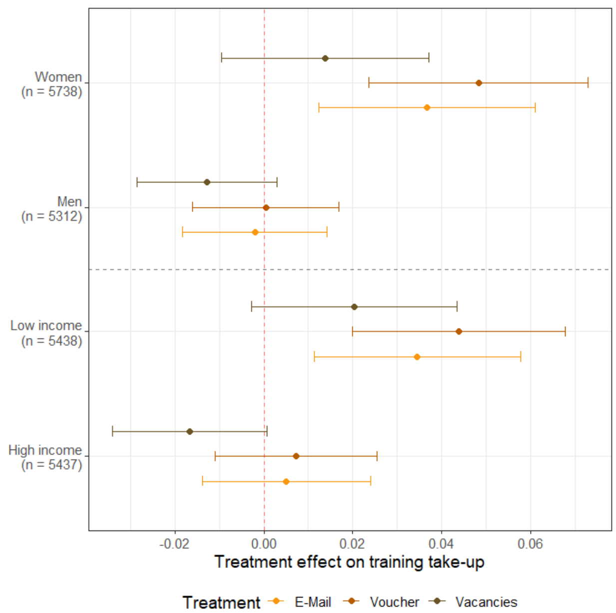
Note: Confidence intervals are reported at the 90%-level.

Heterogeneity To account for heterogeneity, we conducted subgroup regressions of the baseline equation for the main outcome variables (Table 2). The treatment coefficients and 90%-confidence intervals are reported in Figure 4.

The overall positive treatment effect for job seekers who receive vouchers is fully driven by women and unemployed people with lower income (Figure 4). Further, unemployed people older than 35 years, with Austrian citizenship, non-German speaking, and with educational attainment above compulsory schooling contribute to the effect. Heterogeneous effects are similar between providing information (e-mail) and signaling the monetary value on top (voucher).

Treatment 3 (e-mail + voucher + information) results in unexpected diverging outcomes for different subgroups. Contrary to treatments 1 and 2, job seekers with minimum educational attainment tend to react positively, while those above the statutory minimum do not. The intervention has marginally significant positive effects for younger and older job seekers but simultaneously appears to discourage people in core working-age.

Figure 4: Heterogeneity in average treatment effects on training enrollment by gender and income



Note: Confidence intervals are reported at the 90%-level.

Table 2: Heterogeneity in training enrollment by gender and income

	Dependent variable: Training take-up			
	Women	Men	Below median income	Above median income
	(1)	(2)	(3)	(4)
E-Mail	0.034***	−0.002	0.032***	0.005
	(0.013)	(0.010)	(0.012)	(0.011)
Voucher	0.046***	0.0004	0.040***	0.007
	(0.013)	(0.010)	(0.012)	(0.011)
Vacancies	0.012	−0.013	0.018	−0.016
	(0.013)	(0.010)	(0.012)	(0.011)
Control Group Mean	0.137	0.086	0.113	0.102
Control Group SD	0.344	0.28	0.317	0.302
Observations	5,523	5,191	5,363	5,351

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

4.3 Employment

Table 3 reports the results of the 3 treatment arms on employment 15 months after the intervention. To maximize statistical power, we pool individuals in the treatment groups that increase training (treatment groups 1 and 2). Table B11 presents the employment results for the three treatment groups separately. We measure employment with a dummy variable for in employment at any point within 15 months since the intervention (columns 1-2). Participating in a job training program counts as unemployed. Additionally, we use continuous variables for days in employment and days in unemployment (columns 3-4). We also observe wages and job quality. Wages are defined as the average daily wage for individuals who are in employment for the 12 months period after the intervention (column 5). We test a range of alternative definitions for robustness presented in Table B9. Job quality is an equally-weighted indicator for earnings and employment stability.

At baseline, 61% of job seekers in our sample have been in employment within 15 months after the intervention (column 1). Within the 450-day period observed, a job seeker is on average 132 days (29%) in employment (column 3), 242 days (54%) in unemployment (column 4) and the remaining 76 days (17%) out of the labor force. Once in employment, their average wage amounts to 49 Euros gross per calendar day (column 5).

Findings Training programs fail to improve employment status of job seekers within the 15-month period observed. We do not find statistically significant effects. However, viewed together the coefficients point in a negative direction across a range of outcomes and estimation approaches (Table 3). This even pattern suggests negative consequences of training on employment status and wages in the short run. The coefficient for employment status is negative but not statistically significant. Instrumenting training program participation with the information intervention results also in a negative but nonsignificant coefficient for employment status (column 2). On average, job seekers in the treatment group that increased training participation spent 3.5 days less in employment. Days in unemployment also decreased marginally (column 4) driven by labor force exits.[11] Neither wages nor job quality increases with training (columns 5 and 6). The findings are robust across several outcome definitions including income (Table B9), estimation strategies including IV (Table B10), and by observing treatment groups separately (Table B11). Signs of negative employment effects start appearing 5 months after the intervention (Figure B4).

Table 3: Average treatment effects on employment

	Dependent variable:					
	Any employment		Days in employment	Days in unemployment	Avg. daily wage	Jobquality
	(1)	(2)	(3)	(4)	(5)	(6)
E-mail + Voucher	−0.011		−3.221	−0.631	−0.017	0.002
	(0.011)		(3.289)	(3.325)	(0.860)	(0.005)
training		−0.216				
		(0.432)				
Control Group Mean	0.61	0.61	131.986	241.98	48.76	0.36
Control Group SD	0.488	0.488	149.124	145.342	30.172	0.148
Observations	10,714	10,714	10,714	10,714	6,441	5,697

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Heterogeneity We do not find significant heterogeneity in employment but suggestive evidence that disadvantaged groups may benefit from training programs while those with the highest baseline training participation may experience negative employment effects (Appendix B.4). Employment effects tend to be positive for those who are older than 50 years (Table B13) and those who are not fluent in German (Table B14). Employment effects tend to be particularly negative for women (Table B12), people aged 35 to 50 years (Table B13), Austrian citizens (Table B14), and job seekers who previously worked in medium-skilled occupations (Table B15).

5 Mechanisms

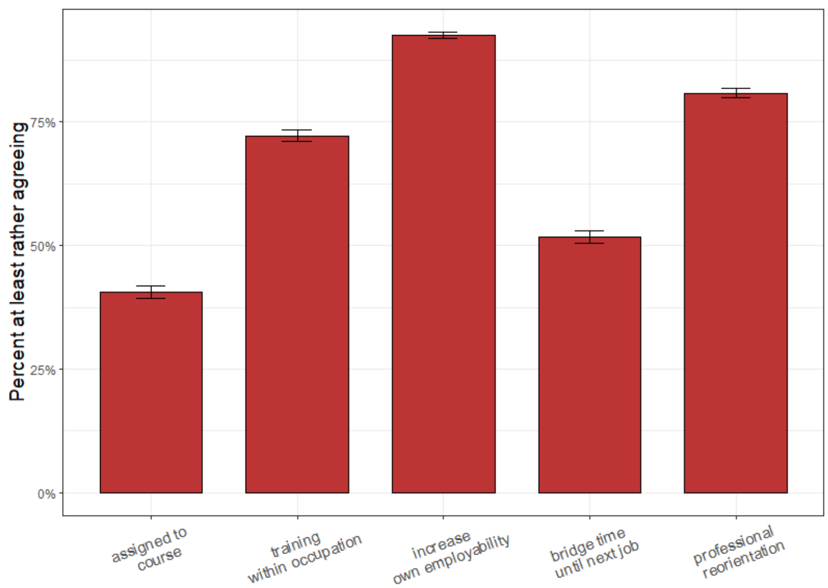
We investigate mechanisms for training behavior by surveying individuals in our sample. Details of the survey design are provided in Section 3 and Section C.1. First, the survey results provide contextual information on job seekers' motivation to enroll in training and to what extent training

[11]The categories employment, unemployment and out of labor force sum up to one.

intentions translate into enrollment. Further, we examine training program assignment and present results on perceived autonomy in program choice affected by the treatments.

Motivation Why do job seekers enroll in training? Desires such as increasing one's employability drive most job seekers enrollment while external constraints such as being assigned to a course drive a sizeable minority. 9 out of 10 job seekers enroll in training to increase their employability (Figure 5). 80% consider professional re-orientation as a motive while for 70% training within their occupation is important. About half of job seekers simply intend to bridge the time until their next job. Assignment by the caseworker as an external factor matters for around 40% of job seekers.

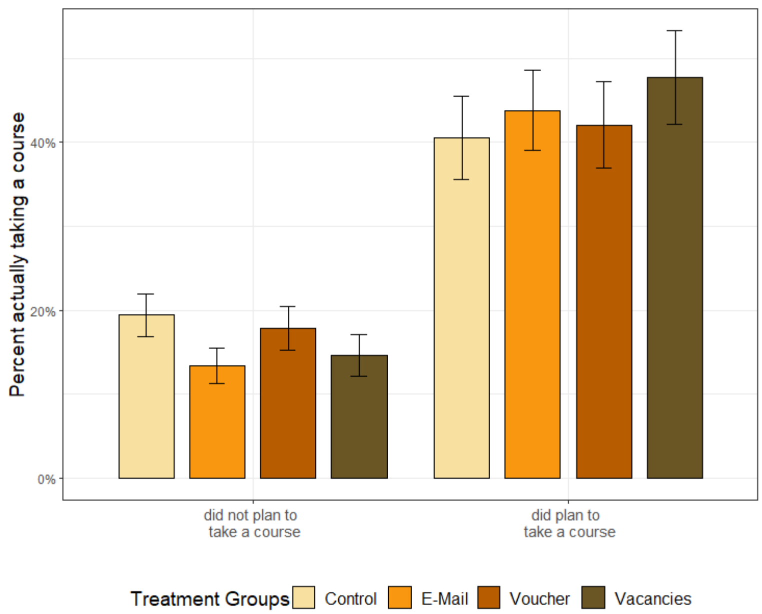
Figure 5: Motivation for training enrollment



Note: Confidence intervals are reported at the 90%-level.

Intentions Intentions for training translate into actual program enrollment (Figure 6). Among job seekers who had plans to take a course, 40%-50% eventually enrolled in a program. By contrast, among those who did not plan to take a course, 10%-20% ended up enrolled in a training program. Some job seekers may have changed their mind or did not follow through on their intentions, which creates some noise around the correlation of intentions and enrollment. Still, job seekers own intentions are found to matter for actual training, which underscored to the discretion on the side of job seekers in deciding whether to enroll in a program. Some of those who intended to enroll may have not been accepted by caseworkers, which we investigate in Table 5. At the same time, the 10%-20% of job seekers who did not intend to train but ended up training may correspond to the 40% of job seekers who enrolled in a course because they were assigned to it (Figure 5). There are no sizable treatment differences in the correlation of intentions and actual training enrolment. However, one may argue that the correlation is lower for the control group, i.e. the share of those who planned to participate and actually participated is slightly lower while the share of those who did not plan to enrol but eventually enrolled is slightly higher than for the other groups.

Figure 6: Training intentions and enrollment



Note: Confidence intervals are reported at the 90%-level.

Autonomy The treatments enhanced job seekers self-assessed autonomy in course assignment (Table 4). Recipients of any treatment felt more in control over which course to choose (column 1). Job seekers who received the voucher also tend to report more often that courses are expensive (column 2), which indicates that the voucher was effective in signalling the monetary value of training programs. Recipients of the e-mail and voucher report less often that they lack information on courses (column 3), which indicates the effectiveness of the treatment in raising awareness and informing job seekers about their training options. In parallel, recipients of the vacancies information tend to report more often that they lack information, which makes us speculate that the information on occupations with job openings may have provided insufficient content to inform job seekers about their options. It has to be kept in mind that the results in column 2 and 3 are not statistically significant, though this could be due to the smaller sample size of those who responded to the survey.

Table 4: Self-assessed autonomy in course assignment

	Dependent variable:		
	Choose own courses	Courses are expensive	Lack information
	(1)	(2)	(3)
E-mail	0.068**	0.017	−0.030
	(0.031)	(0.030)	(0.038)
Voucher	0.069**	0.030	−0.015
	(0.032)	(0.031)	(0.040)
Vacancies	0.091***	0.035	0.054
	(0.032)	(0.031)	(0.040)
Reference Mean	0.362	0.64	0.425
Reference SD	0.481	0.48	0.495
Caseworker Fixed Effects	1	1	0
Observations	1,722	1,722	1,145

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01.

Assignment The increase in perceived autonomy over training enrollment among job seekers led to more discussion among training enrollment with caseworkers (Table 5). Treated job seekers report less often that their wishes for training program assignment were considered by caseworkers (column 1). Reversely, course plans of treated job seekers were more often turned down (column 2). Job seekers felt more autonomy over program choice but were confronted with the reality of required approval by job caseworkers. While this indicates the boundaries of increasing perceived autonomy without changing the formal assignment rules, the treatments suggest to have had some impact on course assignment. Treated job seekers report less often that assignment to a course by a caseworker was a reason for program enrollment (column 3). The increased interest of job seekers for training also resulted in a higher share of job seekers reporting that they could not find a suitable course (column 4). These mechanisms help to understand the imperfect translation of training intentions into enrollment.

Table 5: Training program assignment

	Dependent variable:			
	My wishes are considered	Course was turned down	Assigned to course	Couldn't find suitable course
	(1)	(2)	(3)	(4)
E-mail	−0.054*	0.051	−0.161	0.235
	(0.029)	(0.033)	(0.054)	(0.039)
Voucher	−0.068**	0.105***	−0.573	0.442**
	(0.030)	(0.036)	(0.055)	(0.041)
Vacancies	−0.052*	0.036	−0.316	0.368*
	(0.030)	(0.034)	(0.059)	(0.041)
Reference Mean	0.741	0.225	0.465	0.454
Reference SD	0.439	0.419	0.501	0.499
Caseworker Fixed Effects	1	0	0	0
Observations	1,722	1,145	480	1,145

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01.

Vacancies While the vacancies information did not affect aggregate training behavior, it did increase perceived autonomy and the disconnect between training intentions and behavior. Subgroup analyses show that the vacancies information may have discouraged job seekers from training who are overqualified for the jobs with high demand. Among low educated survey participants, 55% find the information on job openings helpful and nearly 50% are willing to take one of the jobs advertised. For those educated above the minimum, only 35% find the information helpful and only 30% are willing to take on one of the advertised jobs.

6 Discussion

In Section 6.1, we discuss the training results and potential mechanisms, and compare training take-up to related studies. In Section 6.2, we compare our employment results to field experiments with comparable information interventions and discuss limitations of our study.

6.1 Training

The findings are remarkable in three aspects: their large magnitude given a one-off information intervention, the negative effect of vacancy information, and the spillover on enrollment in other active labor market programs. We also reflect on implications from the large heterogeneous response. Investigating these aspects helps to understand the underlying mechanisms.

Magnitude An increase of 18% to 21% from baseline is substantial for a one-off information intervention that consists only of an e-mail. The closest related studies have found null effects of providing and framing information on training enrollment (Dhia and Mbih, 2020; Leduc and Tojerow, 2023) Alike ours, both experiments took place as part of broader PES campaigns to promote job training. Our results are in line with information interventions outside the labor market, which have found larger effects of providing information in mailings. This includes a 35-60% increase in filing applications for social benefits (Bhargava and Manoli, 2015), an increase up to 15% in compliance with municipal housing codes (Linos et al., 2020), an increase up to 11% in registrations of high school students for state scholarships (Linos et al., 2022b), and an 11% increase in rental assistance program applications (Lasky-Fink and Linos, 2022). In an observational study, Barr and Turner (2018) find that information letters increase college enrollment of job seekers in the U.S. by 40%, driven by more vulnerable job seekers.

One may think of several reasons why our experiment was the first to be successful in shifting training enrollment of job seekers. Differences in the approach of caseworkers seem most convincing. First, the design of the e-mail may be more accessible and appealing to job seekers. However, our e-mail (treatment 1) is similar in design and content to Dhia and Mbih (2020); Leduc and Tojerow (2023) and adding the voucher (treatment 2) did not have a large additional effect. Second, contextual factors may have amplified the large effect on training. Indeed, the intervention was implemented during a large-scale expansion of training program supply, which may have lowered the bar for enrollment for job seekers. However, the experiments in Dhia and Mbih (2020); Leduc and Tojerow (2023) took place during similar periods of training expansion-a time suitable for PES to collaborate on information campaigns. Finally, caseworkers need to approve job seekers' assignment to a training program. Increased interest in training from job seekers could either result in increased enrollment, or increased rejection of job seekers' expressions of interest for training. None of the studies collect data on rejection rates of job seekers' training intentions. They do, however, report increases in call-back rates (Dhia and Mbih, 2020) and intentions to enroll in trainings (Leduc and Tojerow, 2023), which did not translate into training enrollment. Activation requirements in France and Belgium are overall not more stringent than in Austria and even more lenient with regard to ALMP participation (OECD, 2023). The dynamic between job seekers and caseworkers could still play a role. Job seekers, for instance, typically express interest in training informally during repeated interactions with their caseworkers. As discussed in Section 2, 87% of caseworkers in Austria report that they assign job seekers to training programs of their choice (Schönherr and Glaser, 2023), which may explain why the intervention in Austria was successful. Our survey will shed light on the power dynamic from the perspective of job seekers.

Unintended consequences The negative effect of the vacancy information (treatment 3) on training enrollment was unintended. The purpose of the treatment was to provide additional information on the labor market to broaden job seekers' search and training choices towards occupations with high labor demand. As most of the jobs with many open vacancies are in low skill occupations, those job seekers with educational attainment above compulsory schooling got discouraged from training, while job seekers with low educational attainment responded positively. Our survey results will provide evidence on how job seekers updated their expectations on the labor market as an underlying mechanism. Medium and high skilled job seekers correct an overly optimistic misbelief on jobs available. Our results show that correcting overoptimistic misbeliefs can have discouraging consequences, which is in line with Miano (2023) and in contrast to Spinnewijn (2015) and Mueller et al. (2021). The unintended consequence also shows the importance of targeting information to specific sub-groups, which we test in a follow-up experiment.

Spillovers Unsurprisingly, encouraging job seekers to engage in training shifts some away from other ALMPs, such as application courses and subsidized employment. The shift may be driven by job seekers' preferences. Our survey documents that job seekers differentiate between different ALMP types in their attitudes. Application courses are more frequently perceived as a disciplining measure while training programs, in particular longer ones, usually involve an active choice of job seekers (cf. Vlandas, 2013).

Heterogeneity Disadvantaged groups drive the aggregate increase in training. Already at baseline, they participate disproportionally. The full increase in training following the intervention comes from women and job seekers on lower income. On the one hand, this reveals a Matthew Effect for job training, where those with better access at the outset benefit most from an expansion in access to educational programs typically increasing inequalities. At the same time, both groups are generally disadvantaged in the labor market and are found to benefit disproportionally from training, which should reduce inequalities (Zweimüller and Winter-Ebmer, 1996; Card et al., 2018).

This trend might stem from an "access bias" that emerges through particular target groups for trainings (Bonoli and Liechti, 2018). For instance, a subset of training programs are specifically aimed at unemployed women re-entering the workforce post-childbirth. A contextual factor may have contributed as well. Women experienced a sharper increase in unemployment than men during the pandemic (Leitner and Tverdostup, 2023).

6.2 Employment

The absence of positive employment effects of training is surprising. We compare our results to related studies and discuss reasons that help understand our findings including possible lock-in effects, contextual factors from the macro environment, and generalizability of individuals driving the effect.

Comparison We do not have directly comparable estimates for employment from other similar experiments, since those even failed to affect program enrollment as described in Section 6.1. Experiments that provided information treatments to improve job-search have delivered mixed results on employment. Providing access to a website targeted to broaden the set of jobs considered delivers null results (Belot et al., 2019). Providing a brochure with job-search advice (Altmann et al., 2018) increases employment by 1-4%. Providing access to a website with resume and cover letter templates increases employment by 8% (Briscese et al., 2020) and instructing job seekers on how to use the career network website LinkedIn by 10% (Wheeler et al., 2022). Magnitudes measured in days remain small where reported similar to our results. During the year after the intervention, job seekers who received the job search brochure worked, on average, for about 1.2 days more than individuals who did not (Altmann et al., 2018).

Lock-in effects Training program participation can divert job seekers' time and attention temporarily from job-search and thereby lengthen unemployment spells. Such lock-in effects of job training programs are widely documented (Lechner and Wunsch, 2009; Lechner et al., 2011). Our observation period to date ends 15 months after the intervention. The positive effects of training may take longer to materialize, even though programs started due to the intervention have almost entirely ended by now. It is possible that the employment effects may eventually turn positive in the long run.

Contextual factors External influences from the macro-environment may stem from the job training quality in Austria, the business cycle and from the Covid pandemic. All three factors make our context a most-likely scenario to expect positive employment results. If employment effects remain absent in this context, it is unlikely that they occur in other settings. First, the Austrian PES is one of the best equipped PES worldwide and job training has long been recognized as an international role model, as outlined in Section 2. Second, high unemployment at the program start is linked to fewer job opportunities, which reduces the negative lock-in effects that occur during training (Lechner and Wunsch, 2009; Card et al., 2018). If positive employment effects remain absent during high unemployment, it is unlikely that training results in positive effect during low unemployment. Third, the intervention took place during winter and a Covid-induced lockdown. Very few job opportunities existed at least until the end of the lockdown in May 2021. Again, if positive employment effects remain absent in times of few open vacancies, it is a stronger result than in times of high labor demand. To compare interactions with contextual factors, we investigate the effects of training over an entire year after the Covid-induced lockdowns in Lehner and Schwarz (2022). The treatment period to encourage job training covers times of high- and low unemployment-to the best of our knowledge the first time in an experimental setting.

Generalizability The employment effects are driven by the subset of job seekers that started training due to the intervention. While some may wonder whether this subset is representative for the entire population of unemployed workers, we argue that it is the job seekers at the margin of training enrollment that are most relevant to understand the potential benefit of job training expansion. Moreover, our experimental set up allows to causally identify the ITT and the LATE contrary to the majority of previously observational ALMP program evaluations (Imbens, 2010).

7 Conclusion

PES across high income countries struggle to attract job seekers to voluntary enroll into training programs. Many are hesitant due to barriers from information frictions and psychological frictions. Our multi-armed field experiments at scale demonstrate the benefits of raising awareness and signaling the monetary value. Raising awareness to reduce information frictions increases program enrollment by 18%. Signaling the monetary value of job training to reduce internalized stigma as a psychological friction increases training enrollment by 21% and completion even by 28%. However, providing information on labor demand can discourage job seekers from enrolling in training programs, in particular those who feel overqualified for jobs with open vacancies. Overall, our findings suggest that information interventions can be effective in reducing barriers to training program enrollment. However, we do not find positive effects of job training on employment or wages.

Outlook Further evaluations should be carried out in other countries and time periods to investigate the surprising absence of positive effects of training on employment. Based on the positive effects on training enrollment, the PES has implemented the most effective treatment on a permanent basis. As part of the implementation, we continue to use random assignment of the most effective intervention (treatment 2, voucher) and targeted information on job vacancies by education (modified version of treatment 3) to investigate the effects of targeted information on training. The follow up field experiment spans an entire year post-pandemic to account for possible distortions from business cycle dynamics, seasonality and the Covid pandemic.

Implications Our study contributes to the literature on information frictions and psychological frictions as barriers to incomplete take-up of social programs. Disadvantaged people often lack awareness of social programs and experience social stigma related to participation. The results provide evidence on the effectiveness of information interventions in reducing such barriers to increase program take-up. The study also contributes to the active labor market policy evaluation literature. The employment results raise questions about the rationale of encouraging job seekers to participate in job training. The findings strengthen the evidence base to design and implement effective training programs for unemployed workers. Overall, our study shows that information provision can help overcome barriers to program participation but governments should prioritize making social programs effectively work for disadvantaged people.

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Appendix

Table of Contents

A Intervention 1: Design

A.1 Background

Data and ALMP evaluations in Austria Austria's PES has access to high-quality data from longitudinal administrative records. Observational evaluations have found training to increase job seekers' re-employment stability (Zweimüller and Winter-Ebmer, 1996). However, no randomized evaluations of training programs have been carried out.[12]

A.2 Sample

Despite the extensive usage of short-time work, the Covid-19 pandemic resulted in a jump in unemployment by over 50% (Table A1). A high share of lay offs took place at the start of the pandemic in March 2023, which explains the higher share of unemployed with a duration of 9-12 months in our sample (columns (1)-(3)). Among them, a higher share had lower educational attainment and a non-Austrian citizenship, while a smaller share had a health restriction compared to the pool of unemployed job seekers before the pandemic. With regard to gender and age, the composition remained broadly the same. Compared to the Austrian average, job seekers in Lower Austria are on average older, higher educated, hold more often Austrian citizenship and have a health restriction (column (4)). The table compares characteristics for job seekers with an unemployment spell of 3-12 months (column (3)), while our sample excludes those with a spell of 4-6 months (column (5)).

[12]The few experimental evaluations of ALMPs in Austria have focused on job-search assistance (Mühlböck et al., 2022; Böheim et al., 2022) and public employment programs (Kasy and Lehner, 2023).

Table A1: Sample representativeness across time and states

	Lower Austria			Austria
	Feb.19	Feb.20	**Feb.21**	Feb.21
Total	5551	6540	**11050**	71487
Gender				
Women	53.4%	51.7%	**51.9%**	49.4%
Men	46.6%	48.3%	**48.1%**	50.6%
Age				
Below 35 years	30.3%	29.7%	**29.9%**	33.4%
35-50 years	37.0%	37.1%	**38.5%**	39.4%
Above 50 years	32.6%	33.1%	**31.5%**	27.1%
Education				
Compulsory education	29.5%	29.0%	**32.5%**	36.3%
Higher than compulsory	70.5%	71.0%	**67.5%**	63.7%
Citizenship				
Austrian Nationality	82.8%	82.0%	**77.9%**	65.7%
Non-Austrian Nationality	17.2%	18.0%	**22.1%**	34.3%
Health				
Health restriction	24.0%	25.8%	**21.3%**	17.5%
No health restriction	76.0%	74.2%	**78.7%**	82.5%
Unemployment duration				
3-4 months unempl.	28.5%	30.9%	**24.3%**	28.8%
6-9 months unempl.	43.0%	40.0%	**33.9%**	28.9%
9-12 months unempl.	28.6%	29.1%	**41.8%**	42.3%
Language skills				
German speaking	89.0%	88.2%	**88.6%**	85.5%
Non-German speaking	11.0%	11.8%	**11.4%**	14.5%
Summary indicators				
Unemployment rate	8.9%	8.7%	**10.0%**	10.7%
In training	16.2%	15.3%	**13.5%**	16.5%

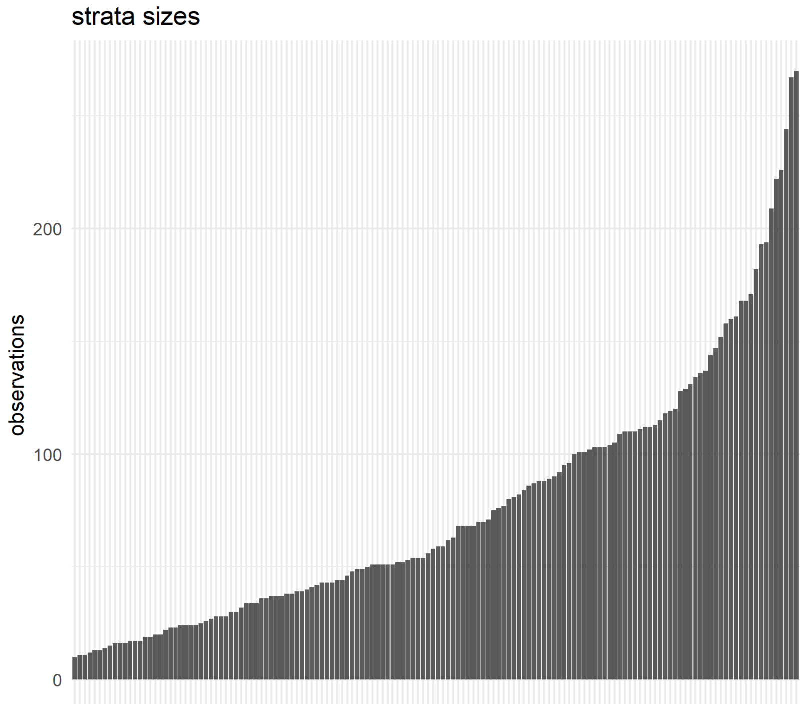
Note: The sample (column (5)) includes only job seekers with 3-4 months unemployment duration as those with 4-6 months were excluded from the experiment. The other columns include job seekers with 3-6 months unemployment duration. All other selection criteria are the same for all columns to correspond to the sample.

A.3 Treatment assignment

Table A2: Balance table

	T1 (N=2769)	T2 (N=2766)	T3 (N=2760)	T4 (N=2755)	Total (N=11050)	p value
Gender						0.999
Women	1437 (51.9%)	1434 (51.8%)	1433 (51.9%)	1434 (52.1%)	5738 (51.9%)	
Men	1332 (48.1%)	1332 (48.2%)	1327 (48.1%)	1321 (47.9%)	5312 (48.1%)	
Age group						1.000
Below 35 years	831 (30.0%)	828 (29.9%)	826 (29.9%)	823 (29.9%)	3308 (29.9%)	
35 - 50 years	1062 (38.4%)	1067 (38.6%)	1064 (38.6%)	1063 (38.6%)	4256 (38.5%)	
Over 50 years	876 (31.6%)	871 (31.5%)	870 (31.5%)	869 (31.5%)	3486 (31.5%)	
Education						1.000
Missing	10	9	8	9	36	
Primary	897 (32.5%)	898 (32.6%)	896 (32.6%)	891 (32.4%)	3582 (32.5%)	
Higher than primary	1862 (67.5%)	1859 (67.4%)	1856 (67.4%)	1855 (67.6%)	7432 (67.5%)	
Region						1.000
Industrieviertel	1222 (44.1%)	1225 (44.3%)	1227 (44.5%)	1219 (44.2%)	4893 (44.3%)	
Mostviertel	741 (26.8%)	731 (26.4%)	732 (26.5%)	732 (26.6%)	2936 (26.6%)	
Waldviertel	243 (8.8%)	245 (8.9%)	239 (8.7%)	241 (8.7%)	968 (8.8%)	
Weinviertel	563 (20.3%)	565 (20.4%)	562 (20.4%)	563 (20.4%)	2253 (20.4%)	
Unemp. dur.						1.000
3 - 4 Months	676 (24.4%)	675 (24.4%)	671 (24.3%)	668 (24.2%)	2690 (24.3%)	
6 - 9 Months	937 (33.8%)	937 (33.9%)	937 (33.9%)	934 (33.9%)	3745 (33.9%)	
9 - 12 Months	1156 (41.7%)	1154 (41.7%)	1152 (41.7%)	1153 (41.9%)	4615 (41.8%)	
Nationality						0.778
Missing	1	2	3	1	7	
Austria	2147 (77.6%)	2146 (77.6%)	2150 (78.0%)	2165 (78.6%)	8608 (77.9%)	
Other	621 (22.4%)	618 (22.4%)	607 (22.0%)	589 (21.4%)	2435 (22.1%)	
Health						0.991
No health restriction	2185 (78.9%)	2177 (78.7%)	2168 (78.6%)	2169 (78.7%)	8699 (78.7%)	
Health restriction	584 (21.1%)	589 (21.3%)	592 (21.4%)	586 (21.3%)	2351 (21.3%)	
Marg. empl.						0.733
No	2457 (88.7%)	2479 (89.6%)	2467 (89.4%)	2463 (89.4%)	9866 (89.3%)	
Yes	312 (11.3%)	287 (10.4%)	293 (10.6%)	292 (10.6%)	1184 (10.7%)	
German						0.456
Partial or non	404 (14.6%)	403 (14.6%)	377 (13.7%)	418 (15.2%)	1602 (14.5%)	
Proficient or native	2365 (85.4%)	2363 (85.4%)	2383 (86.3%)	2337 (84.8%)	9448 (85.5%)	

Figure A1: Strata size



A.4 Treatment (Intervention 1)

Figure A2: E-mail for treatment groups 1, 2 and 3

AMS
Arbeitsmarktservice Niederösterreich

Ihr Weg zum beruflichen Neustart

Sehr geehrte Damen und Herren,

auch jetzt in Zeiten der Krise gibt es nachgefragte Berufe und Qualifikationen mit Zukunft. Die Corona-Joboffensive bietet Ihnen die Möglichkeit, neue Qualifikationen zu erwerben, die Ihnen den Wiedereinstieg ins Berufsleben ermöglichen.

Darum lade ich Sie ganz persönlich ein: Nutzen Sie Ihre Chancen zum beruflichen Neustart mit einer Aus- oder Weiterbildung! Finden Sie gemeinsam mit Ihrer AMS-Beraterin oder Ihrem Berater den für Sie richtigen Weg zurück ins Berufsleben! In diesem Mail zeigen wir Ihnen, wie Ihr beruflicher Neustart gelingen kann.

Nehmen Sie Ihre berufliche Zukunft in die Hand – und bleiben Sie gesund!

Ihr

Sven Hergovich
Landesgeschäftsführer des AMS Niederösterreich

Aus- und Weiterbildung für den Neustart am Arbeitsmarkt

Aktuelle und nachgefragte Qualifikationen sind der wichtigste Erfolgsfaktor für den beruflichen Neustart.

Ob Auffrischungskurs für Ihre Fachkenntnisse oder eine Ausbildung mit Lehrabschluss - das AMS Niederösterreich hält eine Vielzahl von Aus- und Weiterbildungsmöglichkeiten für Sie bereit.

Einige Beispiele:

- Metall- und elektrotechnische Berufe
- Mechatronik
- Berufskraftfahrer/in, Transportwesen
- Pflegeassistenz / Pflegefachasisstenz

Verschaffen Sie sich einen Startvorteil am Arbeitsmarkt und nutzen Sie unsere Aus- und Weiterbildungsangebote!

So finanzieren wir Sie während Ihrer Ausbildung

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Mit dem Schulungsgeld vom AMS sind Sie während der Ausbildung finanziell abgesichert. Der Betrag entspricht zumindest Ihrem Arbeitslosengeld oder Ihrer Notstandshilfe und wird unter bestimmten Voraussetzungen aufgestockt.

Zusätzlich erhalten Sie einen Bildungsbonus in Höhe von 4€ pro Tag, wenn Sie Arbeitslosengeld oder Notstandshilfe beziehen, Ihre Ausbildung zumindest vier Monate dauert und noch in diesem Jahr startet.

Vorsorge und Sicherheit: Ihre Ausbildung während der COVID-19-Maßnahmen

Das AMS nimmt die Situation um die COVID-19-Pandemie ernst. Deswegen passen wir gemeinsam mit unseren Partnerinstituten den Kursbetrieb laufend den gerade erforderlichen Corona-Schutzmaßnahmen an.

Damit Sie gesund bleiben und dennoch Ihre Ausbildung starten können, richtet sich das AMS dabei nach dem Grundsatz:
Soviel Distance Learning wie möglich – so viel Präsenzunterricht wie notwendig!

Informieren Sie sich jetzt!

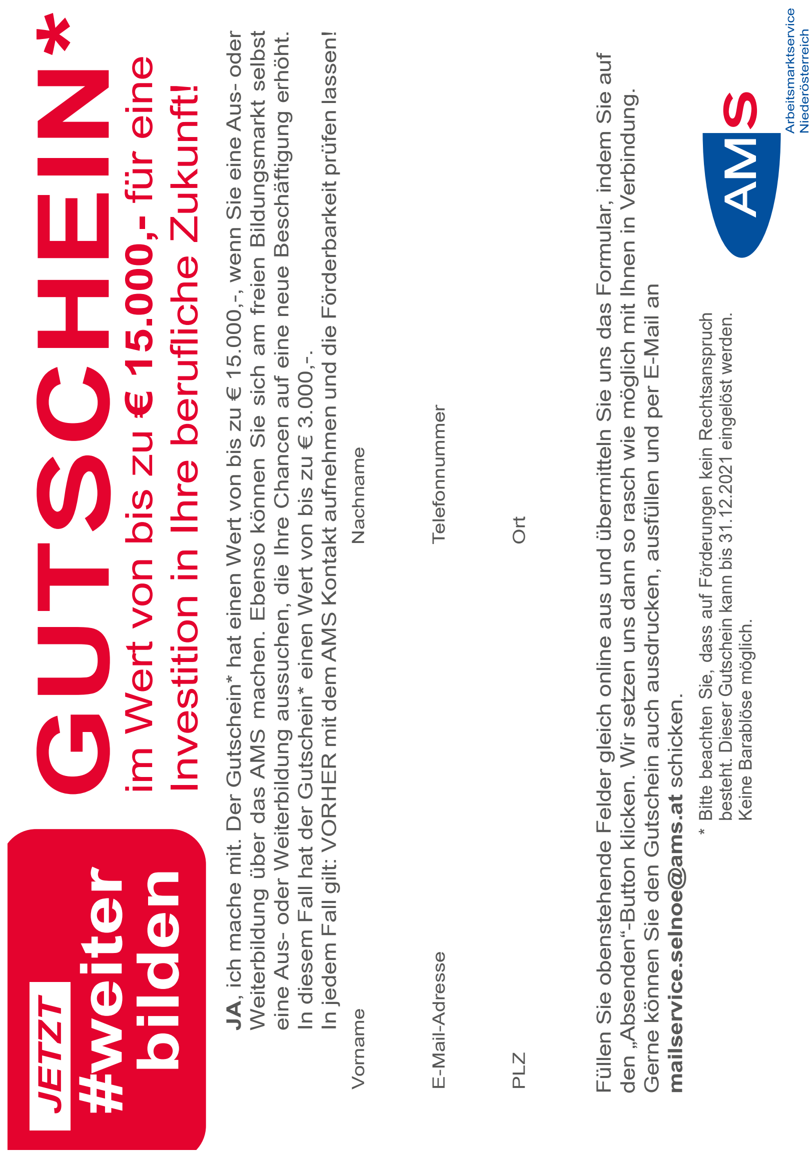
Jetzt informieren unter
050 904 343

Sie möchten mehr über Ihre Weiterbildungsmöglichkeiten erfahren oder wünschen sich Unterstützung bei der Wahl Ihrer passenden Ausbildung?

Unsere ExpertInnen der AMS-Weiterbildungshotline stehen Ihnen bei Fragen montags bis donnerstags von 07:30h bis 16:00h und freitags von 07:30h bis 13:00h unter der Nummer **050 904 343** gerne telefonisch zur Verfügung.

Oder Sie schreiben ein E-Mail.

Figure A3: Voucher for treatment groups 2 and 3



JETZT
#weiter
bilden

GUTSCHEIN*

im Wert von bis zu **€ 15.000,-** für eine
Investition in Ihre berufliche Zukunft!

JA, ich mache mit. Der Gutschein* hat einen Wert von bis zu € 15.000,-, wenn Sie eine Aus- oder Weiterbildung über das AMS machen. Ebenso können Sie sich am freien Bildungsmarkt selbst eine Aus- oder Weiterbildung aussuchen, die Ihre Chancen auf eine neue Beschäftigung erhöht. In diesem Fall hat der Gutschein* einen Wert von bis zu € 3.000,-.
In jedem Fall gilt: VORHER mit dem AMS Kontakt aufnehmen und die Förderbarkeit prüfen lassen!

Vorname	Nachname
E-Mail-Adresse	Telefonnummer
PLZ	Ort

Füllen Sie obenstehende Felder gleich online aus und übermitteln Sie uns das Formular, indem Sie auf den „Absenden“-Button klicken. Wir setzen uns dann so rasch wie möglich mit Ihnen in Verbindung. Gerne können Sie den Gutschein auch ausdrucken, ausfüllen und per E-Mail an **mailservice.selnoe@ams.at** schicken.

* Bitte beachten Sie, dass auf Förderungen kein Rechtsanspruch besteht. Dieser Gutschein kann bis 31.12.2021 eingelöst werden. Keine Barablöse möglich.

AMS
Arbeitsmarktservice
Niederösterreich

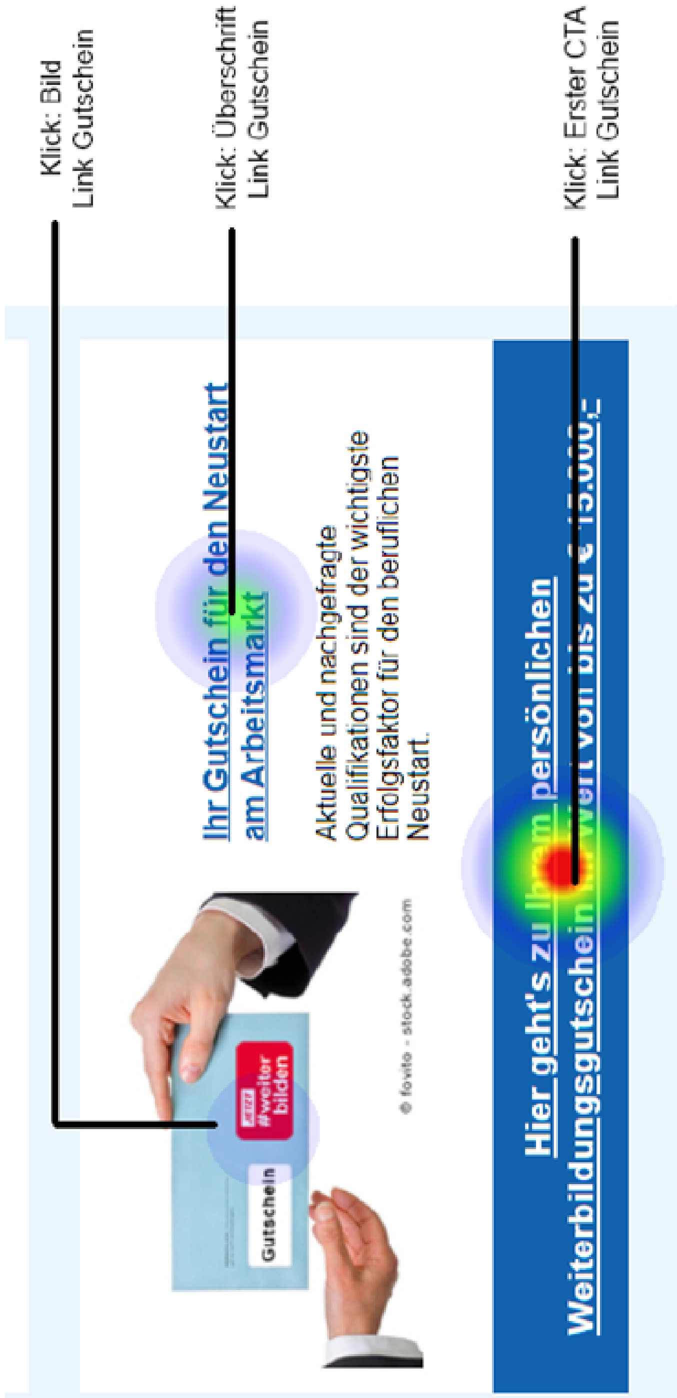
Figure A4: Occupations with the highest number of open vacancies for treatment group 3

Die aktuellen Top Jobs am niederösterreichischen Arbeitsmarkt

- **Elektroinstallateur(e)innen, -monteur(e)innen**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **343**
- **Dipl. Krankenpfleger, -schwestern**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **229**
- **Kraftfahrer/innen (alle Bereiche)**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **228**
- **Maurer/innen**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **170**
- **Techniker/innen für Datenverarbeitung**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **159**
- **Rohrinstallateur(e)innen, -monteur(e)innen**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **157**
- **Hotel- und Gaststättenberufe**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **132**
- **Techniker/innen für Maschinenbau**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **117**
- **Pflegeassistent/in**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **110**
- **Medizinisch-technische Fachkräfte (m./w.)**
  beim AMS NÖ gemeldete offene Stellen im Jänner: **81**

A.5 Tracking e-mail responses

Figure A5: Measurement of e-mail openings and clicks



B Intervention 1: Results

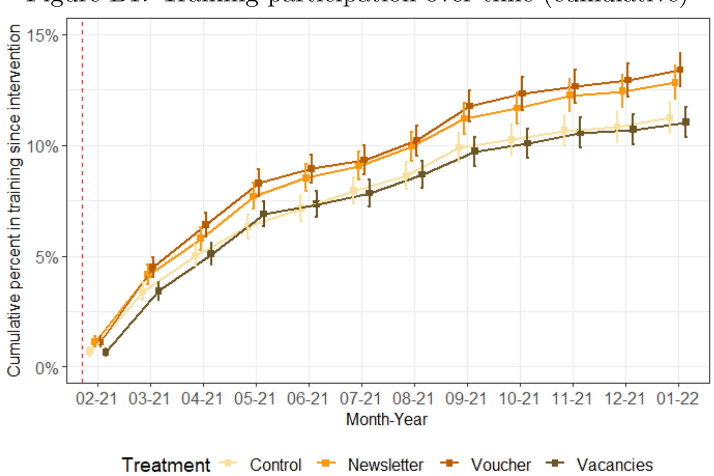
B.1 Training

Table B1: Training completion

	Completion			
	Long training	Examined training	Application courses	External courses
	(1)	(2)	(3)	(4)
E-Mail	0.018**	0.010**	−0.009*	−0.002
	(0.008)	(0.005)	(0.005)	(0.004)
Voucher	0.026***	0.009*	−0.006	0.005
	(0.008)	(0.005)	(0.005)	(0.005)
Vacancies	0.006	0.004	−0.003	0.0001
	(0.008)	(0.005)	(0.005)	(0.005)
Control Mean	0.094	0.033	0.042	0.029
Control SD	0.292	0.177	0.2	0.169
Observations	10,714	10,714	10,714	10,714

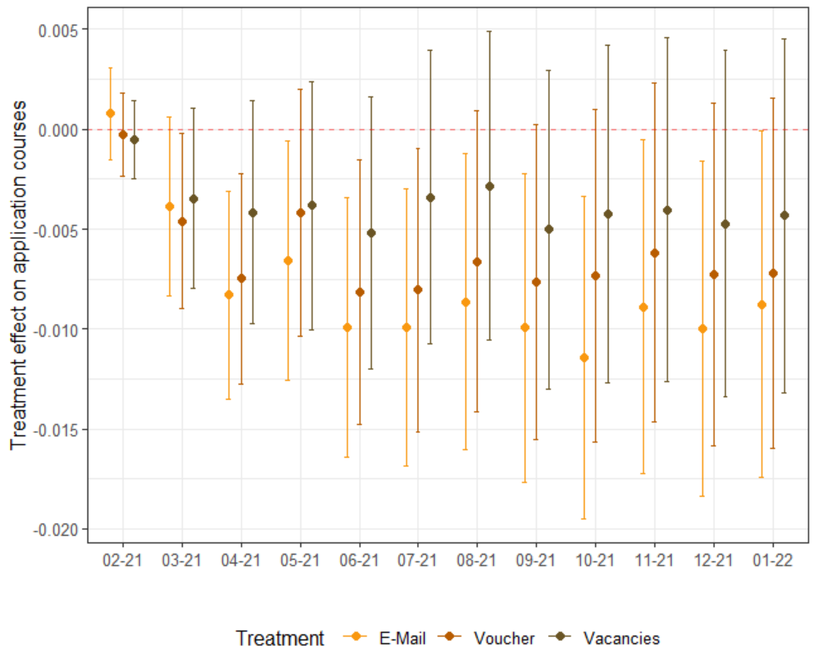
Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Figure B1: Training participation over time (cumulative)



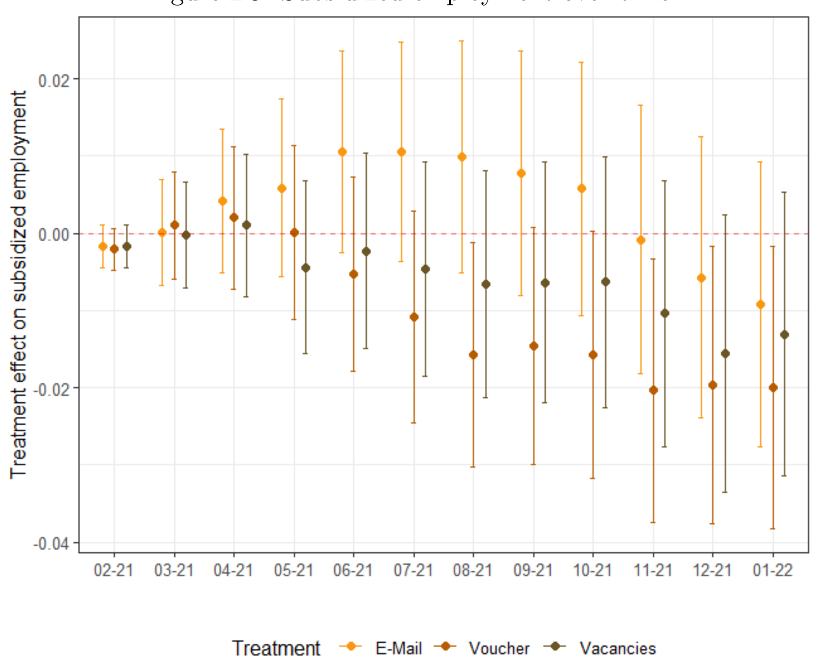
Note: Confidence intervals are reported at the 90%-level.

Figure B2: Application course enrollment over time



Note: Confidence intervals are reported at the 90%-level.

Figure B3: Subsidized employment over time



Note: Confidence intervals are reported at the 90%-level.

B.2 Heterogeneity in training

B.2.1 Training enrollment

Table B2: Heterogeneity in training enrollment by age and education

	Dependent variable:					
	Training Take-up					
	below 35 years	35 to 50 years	Above 50 years	Up to secondary education	Vocational education	More than secondary education
	(1)	(2)	(3)	(4)	(5)	(6)
E-mail	0.003	0.028*	0.021*	0.015	0.026**	0.021**
	(0.017)	(0.015)	(0.011)	(0.014)	(0.013)	(0.013)
Voucher	0.013	0.036**	0.021*	0.027*	0.030**	0.018**
	(0.017)	(0.015)	(0.011)	(0.014)	(0.013)	(0.013)
Vacancies	0.005	−0.013	0.010	0.012	−0.004	−0.001
	(0.017)	(0.014)	(0.011)	(0.014)	(0.012)	(0.012)
Control Group Mean	0.132	0.05	0.153	0.108	0.137	0.086
Control Group SD	0.338	0.219	0.36	0.311	0.344	0.28
Observations	3,169	4,116	3,429	4,350	3,995	2,369

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table B3: Heterogeneity in training enrollment by nationality and language

	Dependent variable:			
	Training Take-up			
	Non-Austrian	Austrian	Non-German speaking	German speaking
	(1)	(2)	(3)	(4)
E-mail	0.031	0.018**	0.058**	0.016*
	(0.022)	(0.009)	(0.029)	(0.008)
Voucher	0.004	0.025***	0.036	0.022***
	(0.022)	(0.009)	(0.030)	(0.008)
Vacancies	0.003	−0.0003	0.029	−0.001
	(0.021)	(0.008)	(0.028)	(0.008)
Control Group Mean	0.196	0.088	0.243	0.09
Control Group SD	0.398	0.283	0.429	0.286
Observations	2,270	8,444	1,460	9,254

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table B4: Heterogeneity in training enrollment by occupation

	Dependent variable:				
	Training Take-up				
	Blue-collar occupation	White-collar occupation	Low-skilled occupation	Medium-skilled occupation	High-skilled occupation
	(1)	(2)	(3)	(4)	(5)
E-mail	0.018	0.020**	0.034	0.035***	−0.016
	(0.015)	(0.010)	(0.021)	(0.011)	(0.014)
Voucher	0.010	0.027***	0.005	0.044***	−0.004
	(0.014)	(0.010)	(0.021)	(0.011)	(0.015)
Vacancies	0.024*	−0.012	0.033	0.012	−0.031**
	(0.014)	(0.010)	(0.020)	(0.011)	(0.014)
Control Group Mean	0.121	0.103	0.101	0.155	0.097
Control Group SD	0.326	0.304	0.301	0.362	0.295
Observations	3,775	6,939	2,132	5,694	2,888

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

B.2.2 Training completion

Table B5: Heterogeneity in training completion by gender and income

	Dependent variable:			
	Training Completion			
	Women	Men	Below median income	Above median income
	(1)	(2)	(3)	(4)
E-Mail	0.030**	0.001	0.035***	−0.001
	(0.012)	(0.009)	(0.011)	(0.011)
Voucher	0.040***	0.012	0.042***	0.009
	(0.013)	(0.009)	(0.012)	(0.011)
Vacancies	0.012	−0.0002	0.026**	−0.014
	(0.012)	(0.009)	(0.011)	(0.010)
Control Group Mean	0.123	0.063	0.094	0.084
Control Group SD	0.329	0.243	0.292	0.278
Observations	5,523	5,191	5,363	5,351

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table B6: Heterogeneity in training completion by age and education

	Dependent variable:					
	Training Completion					
	Below 35 years	35 to 50 years	Above 50 years	Up to secondary education	Vocational education	More than secondary education
	(1)	(2)	(3)	(4)	(5)	(6)
E-mail	0.014	0.017	0.019*	0.015	0.019	0.026
	(0.016)	(0.013)	(0.011)	(0.013)	(0.012)	(0.012)
Voucher	0.017	0.039***	0.017	0.030**	0.026**	0.027**
	(0.016)	(0.014)	(0.011)	(0.013)	(0.012)	(0.012)
Vacancies	0.010	−0.005	0.011	0.013	−0.001	0.017
	(0.015)	(0.013)	(0.010)	(0.013)	(0.011)	(0.011)
Control Group Mean	0.113	0.045	0.123	0.09	0.116	0.071
Control Group SD	0.317	0.206	0.328	0.287	0.32	0.257
Observations	3,169	4,116	3,429	4,350	3,995	2,369

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table B7: Heterogeneity in training completion by nationality and language

	Dependent variable:			
	Training Completion			
	Non-Austrian	Austrian	Non-German speaking	German speaking
	(1)	(2)	(3)	(4)
E-mail	0.058	0.013*	0.032**	0.016*
	(0.021)	(0.008)	(0.028)	(0.008)
Voucher	0.024	0.026***	0.010	0.027***
	(0.020)	(0.008)	(0.028)	(0.008)
Vacancies	0.041	0.003	0.022	0.002
	(0.020)	(0.008)	(0.027)	(0.007)
Control Group Mean	0.169	0.073	0.213	0.074
Control Group SD	0.375	0.26	0.41	0.262
Observations	2,270	8,444	1,460	9,254

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table B8: Heterogeneity in training completion by occupation

	Dependent variable:				
	Training Completion				
	Blue-collar occupation	White-collar occupation	Low-skilled occupation	Medium-skilled occupation	High-skilled occupation
	(1)	(2)	(3)	(4)	(5)
E-mail	0.020	0.017*	0.032*	0.031***	−0.016
	(0.013)	(0.010)	(0.019)	(0.011)	(0.014)
Voucher	0.017	0.028***	0.009	0.043***	−0.004
	(0.013)	(0.010)	(0.019)	(0.011)	(0.014)
Vacancies	0.035***	−0.008	0.045**	0.013	−0.027**
	(0.013)	(0.009)	(0.019)	(0.010)	(0.013)
Control Group Mean	0.099	0.088	0.09	0.125	0.08
Control Group SD	0.299	0.283	0.286	0.332	0.272
Observations	3,775	6,939	2,132	5,694	2,888

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

B.3 Employment

Table B9: Income with alternative definitions

	Dependent variable:			
	Daily wage in first job	Cumulative earnings	Higher than median avg. daily wage	Higher than median jobquality
	(1)	(2)	(3)	(4)
E-mail + Voucher	−0.535	−221.150	0.004	−0.010
	(0.990)	(253.199)	(0.015)	(0.010)
Control Group Mean	55.76	8664.243	0.471	0.269
Control Group SD	33.598	11211.108	0.499	0.444
Observations	6,090	10,714	6,441	10,714

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table B10: Employment outcomes with instrumental variable approach

	Dependent variable:			
	Days in employment IV reg	Days in unemployment IV reg	Avg. daily wage IV reg	Jobquality IV reg
	(1)	(2)	(3)	(4)
training	−90.674	−52.757	16.408	0.181
	(130.371)	(137.897)	(39.712)	(0.296)
Control Group Mean	131.986	241.98	48.76	0.36
Control Group SD	149.124	145.342	30.172	0.148
Observations	10,714	10,714	6,441	5,697

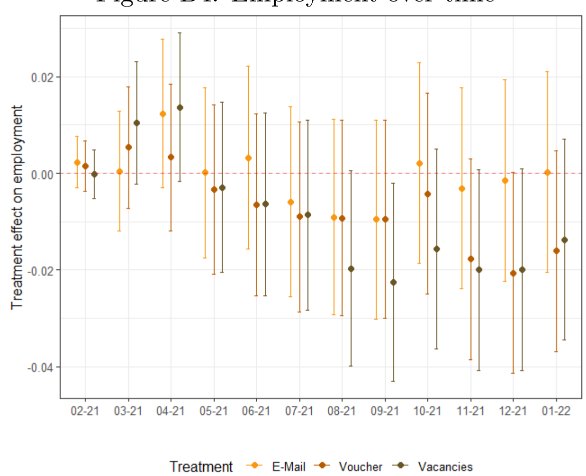
Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table B11: Employment outcomes with separate treatment groups

	Dependent variable:				
	Any employment	Days in employment	Days in unemployment	Avg. daily wage	Jobquality
	(1)	(2)	(3)	(4)	(5)
E-mail	0.001	−3.240	0.321	0.128	−0.002
	(0.012)	(3.790)	(3.840)	(1.008)	(0.005)
Voucher	−0.023*	−3.202	−1.582	−0.165	0.005
	(0.012)	(3.822)	(3.876)	(0.999)	(0.005)
Vacancies	−0.013	−2.567	1.764	−0.262	0.0004
	(0.012)	(3.821)	(3.864)	(1.001)	(0.005)
Control Group Mean	0.61	131.986	241.98	48.76	0.36
Control Group SD	0.488	149.124	145.342	30.172	0.148
Observations	10,714	10,714	10,714	6,441	5,697

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Figure B4: Employment over time



Note: Confidence intervals are reported at the 90%-level.

B.4 Heterogeneity in employment

Table B12: Heterogeneity in employment by gender and income

	Dependent variable:			
	Days in employment			
	Women	Men	Below median income	Above median income
	(1)	(2)	(3)	(4)
E-Mail + Voucher	−4.677	−1.616	−2.933	−2.564
	(4.618)	(4.770)	(4.598)	(4.888)
Control Group Mean	123.551	141.086	125.815	139.775
Control Group SD	148.378	149.447	145.228	153.271
Observations	5,523	5,191	5,363	5,351
Note:	Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01			

Table B13: Heterogeneity in employment by age and education

	Dependent variable:					
	Days in employment					
	Below 35 years	35 to 50 years	Above 50 years	Up to secondary education	Vocational education	More than secondary education
	(1)	(2)	(3)	(4)	(5)	(6)
E-Mail + Voucher	−1.969	−4.594	3.769	−3.261	−4.379	−0.383
	(6.458)	(5.724)	(5.036)	(5.212)	(5.474)	(7.509)
Control Group Mean	154.973	80.297	157.099	136.304	126.177	135.837
Control Group SD	154.107	121.523	155.266	152.348	144.526	151.831
Observations	3,169	4,116	3,429	4,350	3,995	2,369
Note:	Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01					

Table B14: Heterogeneity in employment by nationality and language

	Dependent variable:			
	Days in employment			
	Non-Austrian	Austrian	Non-German speaking	German speaking
	(1)	(2)	(3)	(4)
E-mail + Voucher	1.040	−5.090	4.411	−4.632
	(7.796)	(3.680)	(10.220)	(3.531)
Control Group Mean	141.056	129.387	136.205	131.266
Control Group SD	146.217	149.916	142.564	150.233
Observations	2,270	8,444	1,460	9,254
Note:	Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01			

Table B15: Heterogeneity in employment by occupation

	Dependent variable:				
	Days in employment				
	Blue-collar occupation	White-collar occupation	Low-skilled occupation	Medium-skilled occupation	High-skilled occupation
	(1)	(2)	(3)	(4)	(5)
E-mail + Voucher	−2.780	−3.417	−1.241	−7.334	1.952
	(5.720)	(4.157)	(7.906)	(4.505)	(7.036)
Control Group Mean	130.123	133.321	136.828	123.036	133.36
Control Group SD	146.384	150.651	153.469	142.451	149.403
Observations	3,775	6,939	2,132	5,694	2,888

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

C Survey

C.1 Survey questionnaire

Figure D1: Survey questionnaire: intro

English (United Kingdom)

Intro

Let us know what you think about AMS courses!

Welcome to this short survey on AMS courses at the Vienna University of Economics and Business on behalf of AMS Niederösterreich. In order to be able to tailor the course offer to your interests, please fill out our short survey. Your opinion counts!

The survey only takes 3 minutes. All answers remain completely anonymous. The answers are evaluated by the Vienna University of Economics and Business on behalf of the AMS Niederösterreich and are incorporated into a research project to improve the AMS offer.

Would you like to participate in the survey?

○ Yes, I have been informed of the purpose of the survey and would like to take part.

If you have any questions or comments about the survey or the research project, you can contact me at any time: anna-magdalena.schwarz@wu.ac.at

Figure D2: Survey questionnaire: reminder of treatment

About two months ago you received the following newsletter from the AMS on further training: (please scroll down)

AMS
Arbeitsmarktservice
Niederösterreich

Ihr Weiterbildungsgutschein im Wert von bis zu 15.000,- Euro

Sehr geehrte Damen und Herren,

Nutzen Sie die Chance zum beruflichen Neustart mit einer Qualifizierung im Rahmen der Corona-Joboffensive! Bis zu 15.000,- Euro sind beim AMS Niederösterreich für Ihre zukunftssichere Aus- und Weiterbildung für Sie reserviert.

Finden Sie gemeinsam mit Ihrer AMS-Beraterin oder Ihrem Berater den für Sie richtigen Weg zurück ins Berufsleben und lösen Sie Ihren Weiterbildungsgutschein ein! In diesem Mail zeigen wir Ihnen, wie Ihr beruflicher Neustart gelingen kann.

Nehmen Sie Ihre berufliche Zukunft in die Hand – und bleiben Sie gesund!

Ihr

Sven Hergovich
Landesgeschäftsführer des AMS Niederösterreich

Figure D3: Survey questionnaire: treatment mechanisms

Do you remember that?

Yes ○ No ○

Did the newsletter motivate you to take an AMS course?

Yes very	Yes, rather	Neither nor	No, rather not	no not at all
○	○	○	○	○

Would you take advantage of this offer?

Yes, in any case!	Yes, more likely	Neither nor	No, not really	No, definitely not!
○	○	○	○	○

Would you rather attend an AMS course or a course on the independent education market?

AMS course	More like AMS course	Both	Rather course on the free education market	Course on the free education market
○	○	○	○	○

How did you find the newsletter?

Figure D4: Survey questionnaire: course participation

How decisive were the following factors for you in your decision not to attend a course?

	very important	rather important	Neither nor	not that important	not important at all
The AMS refused my preferred course	◯	◯	◯	◯	◯
I am too old to do advanced training.	◯	◯	◯	◯	◯
I haven't found a suitable course for me	◯	◯	◯	◯	◯

	very important	rather important	Neither nor	not that important	not important at all
I don't have enough information about the AMS courses	◯	◯	◯	◯	◯
I cannot afford to attend a course for financial reasons	◯	◯	◯	◯	◯
I am prevented by other obligations (e.g. childcare or caring for relatives)	◯	◯	◯	◯	◯

C.2 Survey results

Our surveys suggest:

Training course assignment suffers from perverse incentives.

- *"No one cares if a course fits your profile or not. The main focus is that you are no longer adding to the unemployed numbers."*
- *"All pointless mass processing so that some unemployed fall out of the statistics."*
- *"One should be listened to and not just thrown into a course to make the labor market statistics look better."*

Job seekers demand more autonomy.

- *"It would be nice if people's wishes and needs were taken into account."*
- *"Be more responsive to the needs of the unemployed to provide relevant training."*
- *"The PES should provide us with a targeted offer of courses with self-selection under a certain budget, so that we can make our own choices."*

D Intervention 2

This section reports the design and results of intervention 2.

D.1 Design (Intervention 2)

Table D1: Balance table intervention 2

	T1 (N=3440)	T2 (N=3438)	T3 (N=3441)	T4 (N=3445)	Total (N=13764)	p value
Gender						0.999
Women	1656 (48.1%)	1649 (48.0%)	1656 (48.1%)	1655 (48.0%)	6616 (48.1%)	
Men	1784 (51.9%)	1789 (52.0%)	1785 (51.9%)	1790 (52.0%)	7148 (51.9%)	
Age group						1.000
Below 35 years	606 (17.6%)	618 (18.0%)	615 (17.9%)	616 (17.9%)	2455 (17.8%)	
35 - 50 years	1169 (34.0%)	1159 (33.7%)	1163 (33.8%)	1166 (33.8%)	4657 (33.8%)	
Over 50 years	1665 (48.4%)	1661 (48.3%)	1663 (48.3%)	1663 (48.3%)	6652 (48.3%)	
Education						1.000
Missing	10	8	10	12	40	
Primary	1749 (51.0%)	1753 (51.1%)	1752 (51.1%)	1752 (51.0%)	7006 (51.0%)	
Higher than primary	1681 (49.0%)	1677 (48.9%)	1679 (48.9%)	1681 (49.0%)	6718 (49.0%)	
Region						1.000
Industrieviertel	1481 (43.1%)	1481 (43.1%)	1483 (43.1%)	1489 (43.2%)	5934 (43.1%)	
Mostviertel	904 (26.3%)	908 (26.4%)	903 (26.2%)	901 (26.2%)	3616 (26.3%)	
Waldviertel	333 (9.7%)	332 (9.7%)	332 (9.6%)	334 (9.7%)	1331 (9.7%)	
Weinviertel	722 (21.0%)	717 (20.9%)	723 (21.0%)	721 (20.9%)	2883 (20.9%)	
Unemp. dur.						0.934
3 - 4 Months	477 (13.9%)	468 (13.6%)	479 (13.9%)	472 (13.7%)	1896 (13.8%)	
6 - 9 Months	278 (8.1%)	264 (7.7%)	272 (7.9%)	253 (7.3%)	1067 (7.8%)	
9 - 12 Months	299 (8.7%)	316 (9.2%)	307 (8.9%)	334 (9.7%)	1256 (9.1%)	
More than 12 months	2386 (69.4%)	2390 (69.5%)	2383 (69.3%)	2386 (69.3%)	9545 (69.3%)	
Contact						0.998
Post	1775 (51.6%)	1770 (51.5%)	1777 (51.6%)	1781 (51.7%)	7103 (51.6%)	
Email	1665 (48.4%)	1668 (48.5%)	1664 (48.4%)	1664 (48.3%)	6661	
Nationality						0.205
Missing	9	3	7	8	27	
Austria	2514 (73.3%)	2581 (75.1%)	2533 (73.8%)	2578 (75.0%)	10206 (74.3%)	
Other	917 (26.7%)	854 (24.9%)	901 (26.2%)	859 (25.0%)	3531 (25.7%)	
Health						0.839
No health restriction	2202 (64.0%)	2188 (63.6%)	2185 (63.5%)	2221 (64.5%)	8796 (63.9%)	
Health restriction	1238 (36.0%)	1250 (36.4%)	1256 (36.5%)	1224 (35.5%)	4968 (36.1%)	
Marg. empl.						0.493
No	3088 (89.8%)	3058 (88.9%)	3081 (89.5%)	3102 (90.0%)	12329 (89.6%)	
Yes	352 (10.2%)	380 (11.1%)	360 (10.5%)	343 (10.0%)	1435 (10.4%)	
German						0.329
Partial or non	857 (24.9%)	818 (23.8%)	821 (23.9%)	793 (23.0%)	3289 (23.9%)	
Proficient or native	2583 (75.1%)	2620 (76.2%)	2620 (76.1%)	2652 (77.0%)	10475 (76.1%)	

D.2 Treatment (Intervention 2)

Figure D1: Control group: standard text

Bis zu € 15.000,- sind für Ihre Weiterbildung reserviert!

Sehr geehrte Damen und Herren,

Nutzen Sie die Chance zum beruflichen Neustart mit einer Qualifizierung im Rahmen der Corona-Joboffensive! Bis zu € 15.000,- sind beim AMS Niederösterreich für Ihre zukunftssichere Aus- und Weiterbildung für Sie reserviert.

Finden Sie gemeinsam mit Ihrer AMS-Beraterin oder Ihrem Berater den für Sie richtigen Weg zurück ins Berufsleben und lösen Sie Ihren Weiterbildungsgutschein ein! In diesem Mail zeigen wir Ihnen, wie Ihr beruflicher Neustart gelingen kann.

Figure D2: Treatment 1: financial benefits

Bis zu € 15.000,- sind für Ihre Weiterbildung beim AMS für Sie reserviert - machen Sie eine Ausbildung und erhalten Sie bis zu € 1.000,- * Schulungsgeld pro Monat vom AMS!

Sehr geehrte Damen und Herren,

Nutzen Sie die Chance zum beruflichen Neustart mit einer Qualifizierung im Rahmen der Corona-Joboffensive! Bis zu € 15.000,- sind beim AMS Niederösterreich für Ihre zukunftssichere Aus- und Weiterbildung für Sie reserviert.

Bilden Sie sich weiter, erhalten Sie bis zu € 1.000,- * Schulungsgeld pro Monat vom AMS!
Finden Sie gemeinsam mit Ihrer AMS-Beraterin oder Ihrem AMS-Berater den für Sie richtigen Weg zurück ins Berufsleben, lösen Sie den beiliegenden Weiterbildungsgutschein ein und erfahren Sie, wie wir Sie monatlich mit mindestens € 1.000,- * Ausbildungsgeld bei längeren Vollzeitausbildungen unterstützen können.

Figure D3: Treatment 2: training returns

Bis zu € 15.000,- sind für Ihre Weiterbildung beim AMS für Sie reserviert - machen Sie eine Ausbildung und steigern Sie so Ihre Chance auf einen neuen Job um 50%!

Sehr geehrte Damen und Herren,

Nutzen Sie die Chance zum beruflichen Neustart mit einer Qualifizierung im Rahmen der Corona-Joboffensive! Bis zu 15.000,- Euro sind beim AMS Niederösterreich für Ihre zukunftssichere Aus- und Weiterbildung für Sie reserviert.

Mit der richtigen Ausbildung steigern Sie Ihre Chance auf einen neuen Job um 50%!
Finden Sie gemeinsam mit Ihrer AMS-Beraterin oder Ihrem Berater den für Sie richtigen Weg zurück ins Berufsleben und lösen Sie Ihren Weiterbildungsgutschein ein! **Denn mit AMS-Ausbildungen in nachgefragten Berufen steigen Ihre Beschäftigungschancen um 50%**. Gleichzeitig reduziert sich das Risiko, erneut arbeitslos zu werden.

Figure D4: Treatment 3: tailored support

Bis zu € 15.000,- sind für Ihre Weiterbildung beim AMS für Sie reserviert - finden Sie gemeinsam mit Ihrer AMS-Beraterin oder Ihrem AMS-Berater das passende Angebot!

Sehr geehrte Damen und Herren,

Nutzen Sie die Chance zum beruflichen Neustart mit einer Qualifizierung im Rahmen der Corona-Joboffensive! Bis zu 15.000,- Euro sind beim AMS Niederösterreich für Ihre zukunftssichere Aus- und Weiterbildung für Sie reserviert.

Maßgeschneiderte Beratung für eine Weiterbildung, die zu Ihren Fähigkeiten passt.
Sie sind noch nicht sicher, welchen Weg Sie einschlagen möchten? Finden Sie gemeinsam mit Ihrer AMS-Beraterin oder Ihrem AMS Berater den für Sie richtigen Weg zurück uns Berufsleben und lösen Sie den beiliegenden Weiterbildungsgutschein ein.

Nutzen Sie die Möglichkeit einer maßgeschneiderten Beratung, um abgestimmt auf Ihre Wünsche und Fähigkeiten eine für Sie passende Weiterbildung zu finden! In diesem Mail zeigen wir Ihnen, wie Ihr beruflicher Neustart gelingen kann.

D.3 Results (Intervention 2)

Table D2: Training results intervention 2

	Dependent variable:					
	Training	Training completion	Long training	Examined training	Application courses	Subsidized employment
	(1)	(2)	(3)	(4)	(5)	(6)
+ fin. support	−0.008	−0.008	−0.006	0.0002	−0.001	-0.018^{*}
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.010)
+ training benefits	−0.003	−0.005	−0.002	0.004	0.001	0.010
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.010)
+ ind. support	−0.001	0.0004	0.003	0.001	0.005	0.012
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.010)
Control Mean	0.096	0.081	0.065	0.035	0.026	0.224
Control SD	0.295	0.273	0.246	0.185	0.16	0.417
Observations	13,131	13,131	13,131	13,131	13,131	13,131

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01

Table D3: Employment results intervention 2

	Dependent variable:				
	Any employment	Days in employment	Days in unemployment	Avg. daily wage	Jobquality
	(1)	(2)	(3)	(4)	(5)
+ fin. support	−0.014	1.261	0.096	−1.611	0.012^{**}
	(0.011)	(2.641)	(3.327)	(1.058)	(0.006)
+ training benefits	-0.022^{**}	−3.456	2.404	−1.369	−0.002
	(0.011)	(2.567)	(3.306)	(1.047)	(0.006)
+ ind. support	−0.007	−0.652	−1.520	−0.339	0.004
	(0.011)	(2.605)	(3.361)	(1.049)	(0.006)
Control Group Mean	0.416	66.94	265.334	48.435	0.32
Control Group SD	0.493	111.47	139.596	28.823	0.136
Observations	13,131	13,131	13,131	5,620	4,446

Note: Standard errors are in parenthesis: *p<0.1; **p<0.05; ***p<0.01