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Reintegrating Older Long-Term Unemployed Workers: The Impact of Temporary Job Guarantees

Alexander Ahammer, Martin Halla, Pia Heckl, and Rudolf Winter-Ebmer*

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Abstract

Long-term unemployment among older workers is particularly difficult to overcome. We study the impacts of a large-scale job guarantee program that offered up to two years of fully subsidized employment to long-term unemployed individuals aged 50 and above. Using a sharp age-based discontinuity in eligibility, we find that participation increased regular, unsubsidized employment by 43 percentage points two years after the program ended. The gains are driven by transitions into new firms and industries, rather than continued subsidized employment, and we find no evidence of displacement effects for non-participants or spillovers to family members. The program had no measurable short-run health effects.

JEL Classification: J64, J08, J78, I14, H51
Keywords: Long-term unemployment, temporary job guarantee, subsidized employment, health status.

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1 Introduction

Long-term unemployment remains a structural challenge for most OECD countries, with profound implications for both individuals and society.[1] Affected individuals not only endure personal hardships but may also suffer from physical or mental health issues. From a societal perspective, long-term unemployment leads to prolonged underutilization of human capital and necessitates the allocation of resources for unemployment benefits and welfare support. A particularly concerning aspect of long-term unemployment is potential duration dependence in the job-finding rate: the longer individuals remain unemployed, the more difficult it becomes for them to return to work.[2]

This paper presents findings from a large-scale temporary job guarantee program implemented in Austria. In mid-2017, the Austrian government launched a job guarantee initiative aimed at halving long-term unemployment among individuals aged 50 years and older. The program, known as “Aktion 20,000” (hereafter AK20), sought to create 20,000 publicly funded employment positions. Administered through Austria’s *Public Employment Service* (the UI office), it used a detailed matching process to align participants with available positions, primarily in the public and non-profit sector (Hausegger, Krüse, and Hager, 2019). Wages were determined according to collective bargaining agreements, with both wage and non-wage labor costs subsidized by the state. Wages were determined according to collective bargaining agreements, with both wage and non-wage labor costs being fully subsidized. Participants were employed via wage subsidies or within dedicated for-profit and non-profit social enterprises. The job guarantee was limited to a maximum duration of two years for eligible participants.

After only six months, the program was unexpectedly suspended by the newly formed government at the end of 2017.[3] However, applications that had already been approved or submitted were still processed, allowing the program to continue until its planned conclusion in June 2019. Ultimately, the program provided a temporary job guarantee lasting up to two years for a pre-defined group of eligible participants.

We use high-quality administrative data that capture all Austrian workers before and after the implementation of AK20. Our dataset provides daily records on the entire universe of Austrian workers, allowing us to precisely determine employment status and participation in active labor market programs, including AK20. In addition, for workers

[1]In the USA, long-term unemployment is defined by the *Bureau of Labor Statistics* as being unemployed for 27 weeks (approximately 6 months) or more. In Europe, an unemployment duration of 12 months or more is typically used.

[2]Despite significant efforts to address long-term unemployment, many existing active labor market policies have shown limited effectiveness (Card, Kluve, and Weber, 2018). This underscores the pressing need for innovative approaches that can more effectively assist long-term unemployed individuals in reentering the workforce.

[3]The AK20 was a flagship labor market project introduced by the coalition of the *Social Democratic Party of Austria* and the conservative *Austrian People’s Party*. After the 2017 elections, the new coalition of conservatives and right-wing nationalists abruptly halted the AK20 program.

from one of the Austrian states, Upper Austria, we have access to detailed information on healthcare utilization. Since participation in the AK20 program is endogenous, we instrument participation using an age-based eligibility criterion. The strict eligibility rules of AK20 with respect to age enable us to implement a regression discontinuity design (RDD). The unexpected and abrupt suspension of the program (after only half a year) solves the typical issues of "aging into treatment" associated with age-based discontinuities. Given the brief duration of the program, we can address aging into treatment by simply excluding individuals within six months of the age cutoff and estimate a "donut-hole" RDD design. To enhance the credibility of our methodology, we demonstrate that other observable characteristics and pre-program outcomes vary smoothly across the age threshold.

Our results show increases in employment for AK20 participants. One year after the program's initiation, participants are 92 percentage points more likely to be employed, which is mostly due to the subsidized program participation itself. A key strength of our paper is that we can test for employment effects well beyond program participation. After four years, participants have a 43 percentage point higher probability of being employed in the primary labor market. This medium-term effect is not driven by active participation in AK20, since the maximum program duration is two years. We demonstrate that our findings are robust to adjusting the estimation sample and choosing different bandwidths, and they are supported by a two-stage residual inclusion framework, which accounts for the binary nature of the main outcome variable.

The increase in employment is primarily driven by a decrease in unemployment, but also a reduced likelihood of early retirement and marginal employment ("mini-jobs"). Reintegration into the primary labor market is driven by non-subsidized employment rather than subsidized employment. In the two years following the maximum program duration, AK20 participants spend 256 days more in non-subsidized employment and 164 days less in unemployment. When we follow participants in non-subsidized employment after program exit, we see that half of individuals stay in the AK20 firm while the other half move to other firms.

These treatment effects do not vary by sex, education, or prior unemployment length, but that blue-collar workers have stronger positive employment effects compared to white-collar workers. We also test for spillovers on non-participants and families. We find little evidence of spillovers on non-participants, suggesting no substantial general equilibrium effects on the broader population. Within families, spillovers on children appear limited, but we do find a negative effect on spousal retirement, consistent with a joint retirement channel whereby delayed retirement among participants is also associated with later retirement of their spouses.

The success of AK20 probably comes from its ability to address multiple sources of duration dependence. Key mechanisms discussed in the literature include the human capital depreciation during unemployment spells (Mincer and Ofek, 1982; Acemoglu, 1995;

Albrecht et al., 1999),[4] a decline in job search intensity over time (Krueger and Mueller, 2011; Faberman and Kudlyak, 2019), reduced job assignments from employment offices (Winter-Ebmer, 1990), and employer discrimination against the long-term unemployed in the hiring process (for example Oberholzer-Gee, 2008; Kroft, Lange, and Notowidigdo, 2013; Eriksson and Rooth, 2014). Moreover, missing a regular work schedule for a long time may reduce work ethic and reduce employability (Koen, Klehe, and Van Vianen, 2013). Participants in AK20 benefited from actual employment, which not only provided on-the-job training but also enhanced their vitas by removing the stigma of long-term unemployment. Additionally, the employment itself and the clearly defined duration of the program may have incentivized participants to intensify their job search efforts for other opportunities during or after the program's conclusion.

We provide an illustrative back-of-the-envelope calculation showing that, over the first four years after program start, the program generates fiscal benefits amounting to roughly 68% of its direct costs. Given that the average participant entered the program at age 54.6, the accumulation of further fiscal savings prior to retirement makes it plausible that the program could fully break even over the life cycle. Importantly, our analysis of program duration identifies a concrete margin along which costs could be reduced without compromising effectiveness. Using both descriptive comparisons and exogenous variation in potential program duration induced by the program's early termination, we find no evidence that extending participation beyond roughly 16 months yields additional employment gains. This suggests that the maximum program duration could be shortened, offering a clear cost-saving option for policymakers.

The AK20 program can be classified as an active labor market policy (ALMP). Within the framework of standard ALMP terminology, it is best categorized as subsidized employment in the public and non-profit sectors.[5] However, AK20 differs in several key ways from conventional subsidized (private and public) employment programs commonly discussed in the ALMP literature. Most notably, AK20 guaranteed each participant a fully subsidized job for an extended period of time, making it more akin to a temporary job guarantee program.

This paper adds to four strands of the literature. First, it contributes to the understanding of subsidized employment by providing causal evidence on the short- and medium-term effects of a large-scale program. There is consensus that subsidized jobs positively affect employment during active participation, while medium-term effects after program participation are less clear (Cummings and Bloom, 2020). Based on a meta-analysis, Card,

[4] But see Cohen, Johnston, and Lindner (2025), who don't find any decline of cognitive or non-cognitive skills for unemployed workers in Germany.

[5] In their meta-analyses, Card, Kluve, and Weber (2010) and Card, Kluve, and Weber (2018) distinguish between five types of ALMPs: classroom or on-the-job training (42%/49%); job search assistance, monitoring, or sanctions for failing to search (16%/15%); subsidized private sector employment (15%/14%); subsidized public sector employment (14%/9%); and other or a combination of types (15%/14%). The shares in brackets represent the sample proportions in the two meta-analyses.

Kluve, and Weber (2018) conclude that private sector programs generally have modest short-term effects but tend to yield more positive outcomes over the medium and long term. In contrast, subsidized public sector employment programs tend to be relatively ineffective across all time horizons. A key takeaway from the literature is that the type of employment significantly influences outcomes. Jobs with the potential for direct hiring or those in the private sector positively impact long-term labor market outcomes, whereas subsidized employment in non-profit organizations tends to lock in participants, leading to continuous spells in temporary jobs (Gerfin, Lechner, and Steiger, 2005; Autor and Houseman, 2010). This is also highlighted by Mörk, Ottosson, and Vikman (2022) who focus on a temporary subsidized employment program for social assistance recipients in Stockholm who got newly created outdoor workplaces, like picking litter or clearing snow, and find that programs providing jobs in more regular workplaces have positive medium-term effects on employment while those in specifically created workplaces relocate participants into unemployment. Our results indicating a positive impact of subsidized employment in both the short- and medium-term are in line with their findings. We are further able to differentiate between different types of employment and demonstrate that while the initial effect is driven by subsidized employment while actively participating in the program, the persistent positive long-term effects are driven by workers moving into non-subsidized employment. Our paper further adds evidence that the program had no spillover effects.[6]

Second, this paper contributes to the scarce literature on job guarantees. Unlike traditional ALMPs, job guarantee programs have garnered more attention from international organizations and think tanks but have been studied less extensively in the economics literature.[7] Although several evaluations of job guarantee programs exist for the public sector in low-income countries,[8] we are aware of only one study conducted in a high-income country. Kasy and Lehner (2025) study the impact of a local job guarantee program (MAGMA) implemented in a small municipality in Austria for long-term unemployed workers. A common goal of the MAGMA program and the AK20 program was to reduce long-term unemployment, but with a somewhat different focus: while the AK20 program aimed to offer temporary publicly funded positions and foster the re-integration of participants into the primary labor market, re-entry was encouraged but not the main goal of

[6]The analysis of spillover effects has received more attention in recent studies on active labor market policies (Le Barbanchon, Schmieder, and Weber, 2024).

[7]For discussions outside of the academic literature, see, for instance, Paul, Darity, Jr., and Hamilton (2018), International Labour Organization (2018), OECD (2021), United Nations (2023), and Markowitsch and Scharle (2024).

[8]For instance, the *National Rural Employment Guarantee Act* provides guaranteed work for 100 days per year to all rural households in India at a market wage or higher with the goal to reduce poverty. Imbert and Papp (2015) and Muralidharan, Niehaus, and Sukhtankar (2023) show that the program has positive effects on employment and earnings, but crowds out private employment. There are also recent evaluations of public employment schemes for Malawi (Beegle, Galasso, and Goldberg, 2017), and Ivory Coast (Bertrand et al., 2021). For an overview on public works programs see Gehrke and Hartwig (2018).

the MAGMA program. In line with the goals of MAGMA, the experimental evaluation by Kasy and Lehner (2025) focuses on the impact of the job guarantee program on individuals' employment during active participation, non-economic benefits, and community welfare. They find that enrollment in the MAGMA program is high and that participation improves employment during the program as well as income and well-being. We complement and extend their evidence in four ways. First, the MAGMA RCT is relatively small (with around 60 participants), while we study a much larger-scale program that was implemented nationwide. Second, while the employment analysis in Kasy and Lehner (2025) focuses on the program period, we can follow participants well beyond program conclusion to test whether they reintegrate persistently into the primary labor market. Third, we add to the well-being evidence by examining health-related outcomes, including healthcare utilization and antidepressant take-up. Fourth, beyond potential employment effects on non-participants, the breadth of our data allows us to study within-family spillovers.

Third, we contribute to the literature on the impact of ALMPs (in particular, subsidized employment) on health and healthcare utilization. ALMPs may contribute positively to physical or mental health of participants by imposing structured time use and improving social integration through formal employment. On the other hand, work stress may be detrimental to health. Evidence on how participation in ALMPs affects health outcomes is limited, and — similar to employment effects — the impact varies depending on the type of program.[9] We do not observe statistically significant or economically meaningful changes in healthcare expenditures, including inpatient care, outpatient care, and prescription drugs, during program participation. However, due to data limitations, our analysis covers only the first 17 months of the program, preventing us from assessing longer-term health outcomes.

Fourth, this paper contributes to the literature on family spillovers of public programs. While program participation can directly influence the take-up of similar programs (e.g., other ALMPs or subsidized employment) among relatives, the resulting changes in employment and retirement probability may also alter household labor allocation or retirement decisions of other family members (Blau, 1998a; Kugler et al., 2022; Dahl, Kostøl, and Mogstad, 2014; Schlosser and Shanan, 2025). While spillovers on children appear limited, we find a negative effect on spousal retirement, consistent with a joint retirement channel in which delayed retirement among participants is associated with later retirement of their spouses.

[9] For example, training reduces the likelihood cardiovascular and mental health drug use, while sanctions have no significant effect on healthcare utilization (Caliendo et al., 2023). Bastiaans, Dur, and Gielen (2024) show that a more general activation program for long-term welfare recipients lowers mental health drug prescriptions, but only among men previously prescribed such medication. For a subsidized employment program, Mörk, Ottosson, and Vikman (2022) find that participants are less likely to be prescribed psychiatric drugs and experience fewer hospitalizations both during the program and up to two years afterwards. Ahammer and Packham (2023) show that longer unemployment insurance duration can improve mental health for women.

Our paper proceeds as follows. In Section 2, we provide an overview of the relevant institutional background. Section 3 describes our data sources, while Section 4 outlines the analysis samples and presents descriptive statistics. In Section 5, we introduce our estimation strategy and discuss the underlying identification assumptions. Section 6 presents our main findings. We begin by analyzing employment outcomes and examining the robustness of our results. We then explore treatment effect heterogeneity, investigate the mechanisms behind AK20's effectiveness in reintegrating older workers, and test for potential spillover effects on non-eligible individuals and family members. We also assess the program's impact on health outcomes, and finally assess the program's cost effectiveness (Section 7). Section 8 concludes.

2 Institutional background

In this section, we briefly discuss the unemployment insurance system in Austria and long-term unemployment. Next, we describe the job guarantee program AK20 and provide descriptive statistics on its regional coverage, eligibility criteria, and duration.

2.1 Unemployment insurance in Austria

The unemployment insurance (UI) program in Austria covers all workers whose earnings exceed the marginal employment threshold (which was 518.44 € in 2024). It is financed through payroll contributions paid jointly by workers and employers. Eligible unemployed workers generally receive 55% of their prior net income, based on their pre-unemployment wages. Supplements are available for dependents, and the total benefit is capped at a statutory maximum. Benefit duration depends on employment history and age.[10] Once UI benefits are exhausted, individuals may qualify for means-tested unemployment assistance, which extends income support indefinitely, subject to periodic reassessments.

2.2 Long-term unemployment in Austria

Individuals registered as unemployed for more than 365 consecutive days with Austria's *Public Employment Service* (in German: *Arbeitsmarktservice*, AMS hereafter) are considered long-term unemployed.[11] Between 2008 and 2017, Austria experienced a substantial

[10] The standard benefit duration is 20 weeks after at least 52 weeks of employment within the last two years. Workers aged 50+ with at least nine years of employment within the past 15 years are eligible for up to 52 weeks of benefits.

[11] The AMS distinguishes between long-term unemployment and long-term joblessness. The former is defined as individuals who have been registered as unemployed for more than 365 days with the UI office, including short breaks of up to 28 days due to sickness, short employment spells, or training. The latter refers to individuals who have been registered with the UI office for over 365 days, with interruptions of up to 62 days (AMS, 2025). While eligibility for the AK20 program was based on the less stringent criteria of long-term joblessness, we use the more general term long-term unemployment throughout the paper.

increase in long-term unemployment. In 2008, there were only around 34,500 long-term unemployed individuals, but by 2017, the number had risen to 126,788. Thus, the number of long-term unemployed individuals more than tripled in just eight years. As a share of all unemployed, the long-term unemployed increased from 24.3% to 33.4% over this time span. After 2017, the number and share of long-term unemployed began to decrease again. With the exception of these peak years, the Austrian share of long-term unemployed is typically below the OECD average, which ranged between 23.0% and 34.1% over this period (OECD, 2024).

2.3 The job guarantee program "Aktion 20,000"

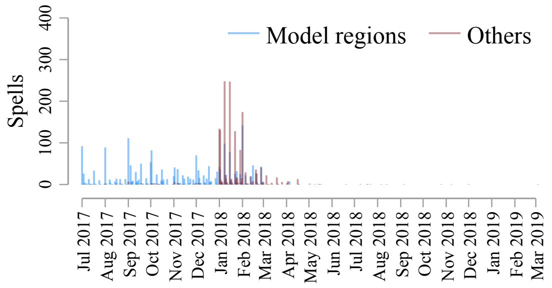
In 2017, the Austrian government, led by a coalition of social democrats and conservatives, launched the AK20 job guarantee program. Its goal was to address the surging long-term unemployment rate and reduce it among older people by half. As its name indicates, the aim of AK20 was to offer 20,000 employment positions for eligible individuals (Hausegger, Krüse, and Hager, 2019; Walch and Dorofeenko, 2020; Picek, 2020).

AK20 was implemented through the AMS on the basis of a detailed matching process between participants and open positions. Eligibility was based on being at least 50 years old and experiencing long-term unemployment. The program provided 100 percent of wage compensation for eligible individuals, including both wage and non-wage labor costs. The wages paid corresponded to collectively bargained wage agreements at the sectoral level. Participants could be directly employed based on wage subsidies or employed at dedicated for-profit and non-profit social enterprises. A proclaimed goal of the AK20 was the creation of additional and meaningful positions. To this end, potential positions were evaluated in terms of whether they were not too closely a substitute for an existing job. Jobs in the program had to be either full-time positions or part-time positions with at least 30 hours per week.

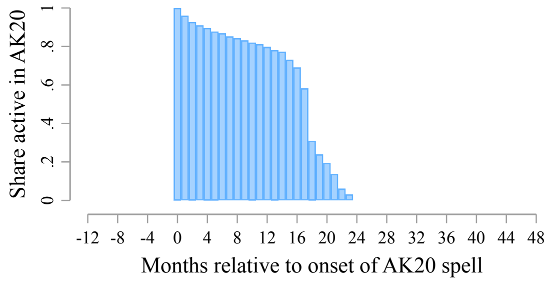
The policy was enacted on June 29, 2017, with an initial budget of up to 778 € million until June 30, 2019. The program began with a pilot phase that ran from July to December 2017. During this phase, it was implemented in one pilot region per Austrian federal state, where "region" corresponds to a political district (see Appendix Figure A.1). The next step, based on insights from the pilot phase, would have been a national rollout of the program starting in January 2018. However, following the 2017 elections, the newly formed coalition government between conservatives and right-wing nationalists abruptly discontinued the AK20 program. Individuals who had already enrolled were allowed to remain in the program until its planned conclusion in June 2019, and applications submitted by the end of 2017 were still processed. As part of the initial rollout, enrollment applications from non-model regions were also accepted, which led to program starts in these regions after January 1, 2018. After that date no new applications were accepted.

In total, 3,815 individuals participated in the AK20 program.

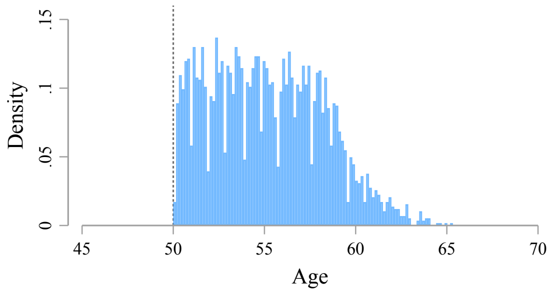
Figure 1: AK20 program participants: Regional variation, duration of participation, age, and previous labor market attachment



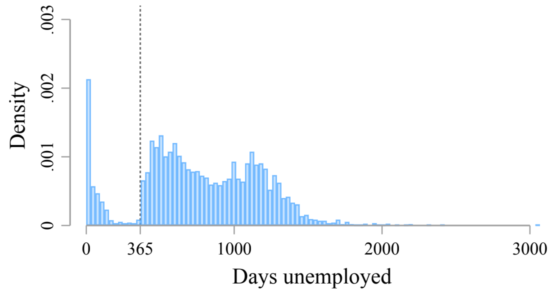
(a) AK20 participants (per spell) in model regions (blue) and non-model regions (red)



(b) Share of workers active in AK20 over time



(c) Age at first AK20 spell



(d) Days in unemployment prior to first AK20 spell

Notes: Figure 1a shows AK20 spell starts over time, differentiating between individuals in model regions (blue) and those in other regions (red). Contrary to the program stipulations, some UI offices in non-model regions were allowed to admit individuals into A20. Figure 1b presents the share of workers active in the AK20 program over time (relative to the onset of the AK20 spell), expressed as a percentage of all AK20 participants. For the subsample of AK20 participants, Figure 1c shows the age distribution of participants at the time of their first AK20 spell and 1d the number of days in unemployment prior to the first AK20 spell.

The majority of AK20 participants were employed in firms operating in the social and health sector, with nearly half of all positions offered in human health and social work activities. Public administration accounted for about a quarter of placements, followed by administrative and support service activities and other service activities.[12]

Figure 1a shows spell starts of AK20 participation over time. Between July 2017 and December 2017, most spells occurred within model regions. However, we also observe a few spell starts in non-model regions in the first six months, which indicates that the lagged roll-out was not strictly adhered to. From January 2018 onward, the majority of new participants entering the AK20 program were from outside the model regions. Especially in non-model regions, a large share of individuals started their participation in

[12]A detailed breakdown of participant shares by industry is provided in Appendix Table A.1.

the program within the first two months.[13]

While participation in the program was planned for a maximum of two years, Figure 1b reveals that only a small share of participants actually stayed in the program for the full two years. After 17 months, more than half of the initially included workers were no longer actively participating in the program. This can be partly explained by the official end of the program in June 2019. Thus, individuals who started the program from January 2018 onwards could join the program for a maximum of 18 months (see Section 7.1).

Figures 1c and 1d refer to the eligibility criteria: age and long-term unemployment. The age threshold at the start of the first AK20 spell (see Figure 1c) of 50 years is strictly enforced. In contrast, the threshold for days in long-term unemployment prior to the first AK20 spell (see Figure 1d) is not fully adhered to. Specifically, 12% of participants had unemployment spells shorter than 365 days. We have verified the accuracy of our data with AMS. It appears that some workers were simply assigned by AMS despite not fulfilling the second criterion. In our analysis, we concentrate on age as the relevant cut-off variable in our RDD approach. In our baseline sample, we include individuals who do not formally meet the long-term unemployment cut-off, but verify that their exclusion does not change our results (see Appendix Table A.4).

3 Data sources

To estimate the effects of AK20 on labor market outcomes, we combine the *Austrian Social Security Database* (ASSD) with data from AMS. The ASSD consists of administrative records used to verify pension claims and is structured as a matched employer-employee dataset. For each worker, we observe daily data on their workplace and co-workers. We also capture socio-economic characteristics, such as age, broad occupation, experience, tenure, and earnings, with earnings provided annually and by employer. The data limitations include top-coded wages and the absence of information on working hours (Zweimüller et al., 2009). However, both aspects are not significant in our context. The AMS data include daily information on unemployment spells and program participation from 2003 to 2021.

To estimate the effects of the program on health, we use administrative data from the *Austrian Health Insurance Fund* (*Österreichische Gesundheitskasse*, hereafter ÖGK). The ÖGK is the main mandatory health insurance provider, covering approximately 82% of the population, including the vast majority of employees, their dependents, and all non-employed residents.[14] We have access to ÖGK data for the entire population of Upper

[13] Walch and Dorofeenko (2020) discuss preparations by the local public employment service offices before the nation-wide rollout that enabled an immediate start of participants in the program.

[14] The remaining 18% are insured through other statutory health insurance providers, including those in specific occupational groups (civil servants, miners, and federal railway employees), as well as the self-employed, freelance professionals, and farmers. Notably, most public sector employees are not civil

Austria from 1998 to 2018.[15] These data include comprehensive records on prescription drugs, physician visits, and hospital stays.

4 Estimation sample

We construct a monthly panel of all AK20 participants and long-term unemployed workers between 46 and 54 years of age. Age is measured as of July 1, 2017.[16] For AK20 participants, the treatment month is defined as the month in which the participant enters the program. For non-participants, we assign a placebo treatment month of July 2017.[17] We follow all individuals from 12 months before to 48 months after the treatment month and merge information on regular employment from the ASSD with information on subsidized employment from the AMS.

Table 1 summarizes the main estimation sample. Column (1) reports statistics for eligible individuals (N = 17,831), Column (2) for non-eligible individuals (N = 13,193), and Column (3) for AK20 participants (N = 1,538), who form a subset of the eligible group. Because of our age restriction (below 54), the estimation sample includes only 1,538 of the full 3,815 AK20 participants.

Eligible individuals are those aged 50 or older, while non-eligible individuals are between ages 46 and 50. As expected, eligible individuals are on average around four years older than non-eligible individuals. Although there are differences in sample means across age groups, we will show below that none of these variables exhibits a discontinuous jump at the age threshold.

AK20 participants appear to be somewhat positively selected: they have higher educational attainment, more prior employment, and fewer prior unemployment days than the average eligible individual. This underscores the importance of addressing endogeneity concerns. Moreover, AK20 participants are more likely to reside in pilot regions. Appendix Table A.1 indicates that the industry distribution of AK20 participants in the estimation sample closely mirrors that of the full AK20 population (column (1) and (2)). Figure 2 depicts the share of individuals with a certain labor market status before and after the start of their (placebo) AK20 spell, separately for eligible, non-eligible, and AK20 participants. By construction of the sample, before the start of the (placebo) AK20 spell, the majority of eligible and non-eligible individuals were unemployed, with 99% of both eligible and

servants and are therefore insured with the ÖGK.

[15]Upper Austria is one of Austria's nine federal states and accounts for approximately one-sixth of the country's population and workforce. Traditionally, each state had its own regional health insurance fund. In 2020, the government merged the nine regional funds into the ÖGK. Our research cooperation is with the Upper Austrian branch.

[16]Birth month is missing for about 10% of unemployed workers in our sample (excluding AK20 participants). For these individuals, birth month is randomly imputed from a uniform integer distribution between one and twelve.

[17]In Section 6.2, we show results using alternative placebo treatment months for non-participants.

Table 1: Descriptive statistics for main estimation sample

	(1) Eligible	(2) Non eligible	(3) AK20 participants
Age	52.03	47.76	52.09
	(1.18)	(1.01)	(1.14)
Female	0.43	0.47	0.49
High school degree or higher	0.28	0.32	0.33
Prior days employed	2901.96	2602.97	3375.41
	(1974.82)	(1938.38)	(1858.11)
Prior days unemployed	2424.59	2276.00	2319.50
	(1556.24)	(1525.10)	(1388.22)
Model region	0.53	0.57	0.61
Number of observations	17,831	13,966	1,538

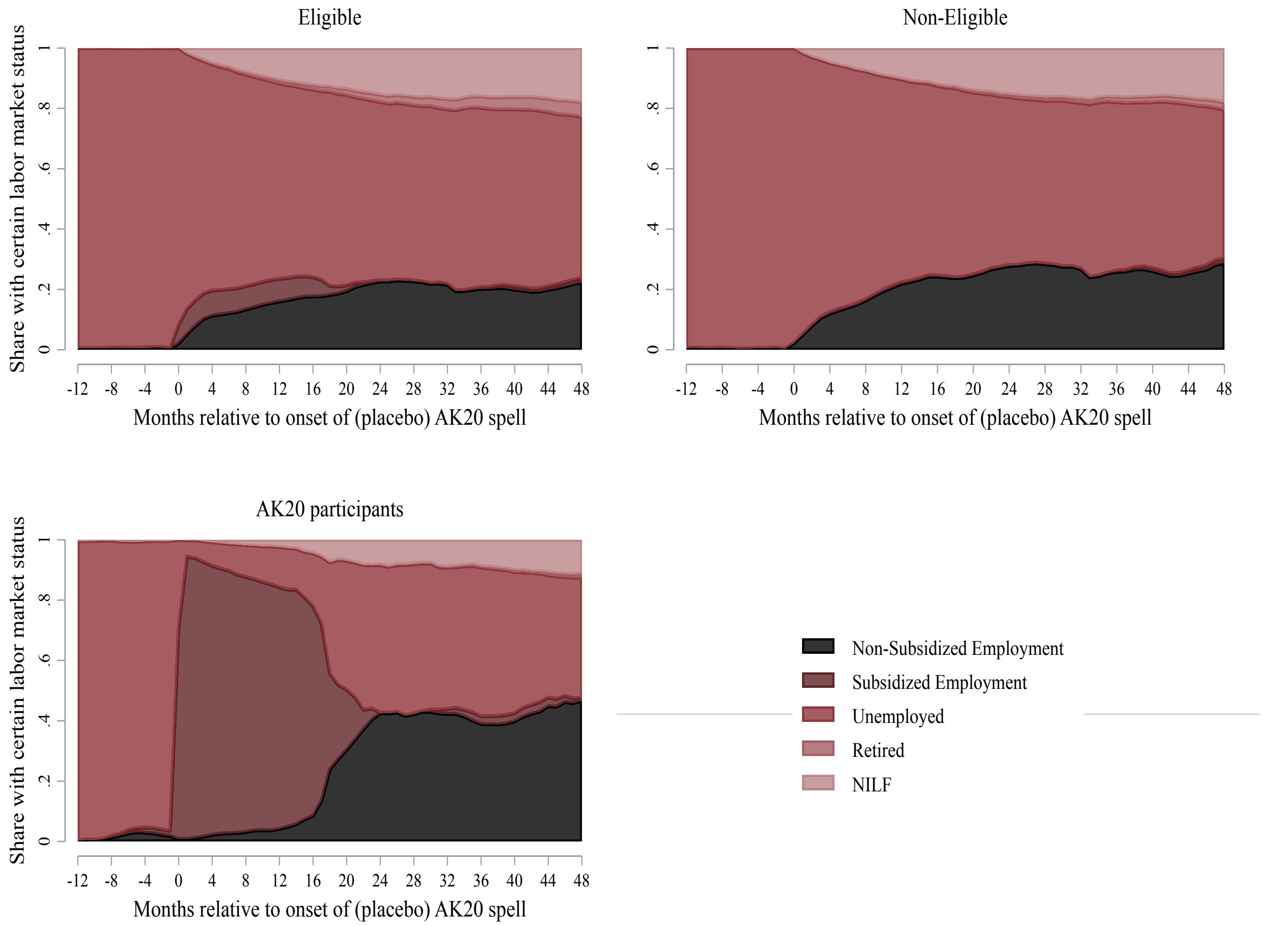
Notes: Table 1 presents summary statistics for the main estimation sample. This sample comprises all AK20 participants and long-term unemployed workers between 46 and 54 years of age. Column 1 reports statistics for eligible individuals, Column 2 for non-eligible individuals, and Column 3 for AK20 participants (a subset of the eligible group). Each cell displays the arithmetic mean, with standard deviations shown in parentheses below for non-binary variables. Prior days employed and prior days unemployed are measured relative to July 2017, which marks the start of the AK20 spell (for participants) or the corresponding placebo spell (for non-participants).

non-eligible individuals being unemployed, on average, during the pre-treatment period.[18] Over time, the share of both eligible and non-eligible individuals in retirement (including early retirement and disability pension) increases. Additionally, the share of individuals who exit the labor force (NILF) rises for both groups alike.

These trends are similar for AK20 participants, who form a subgroup of all eligible individuals. At the start of the AK20 spell, the share of individuals in subsidized employment increases, while the share in unemployment decreases. After around 17 months, the figure reveals a shift from subsidized employment to both non-subsidized employment and unemployment. However, over 40 percent of AK20 participants found their way back to non-subsidized employment after 24 months, while the corresponding share among ineligible individuals is 28 percent. In the following, we test whether, and to what extent, this difference reflects a causal effect of the program.

[18] According to the AMS definition, unemployment spells can be interrupted by short employment episodes of up to 62 days and still be classified as uninterrupted spells. As a result, we observe a small but non-zero probability of employment in the pre-program period.

Figure 2: Labor market status over time



Notes: Figure 2 shows the share of people with a specific labor market status over time relative to the onset of the (placebo) AK20 spell. for eligible individuals, non-eligible individuals, and AK20 participants. Eligibility is based on age: individuals aged 50 years and older are considered eligible, while those under 50 years old are considered non-eligible. Retirement includes regular retirement, early retirement, and disability pension. NILF stands for "Not in labor force".

5 Research design

We estimate the impact of the job guarantee program AK20 using an RDD approach, exploiting the discontinuity in eligibility at age 50. The abrupt suspension of the program solves the typical issues of "aging into treatment" associated with age-based discontinuities. Given the brief duration of the program, we can simply address "aging into treatment" by excluding individuals within six months of the age cutoff and estimate a "donut-hole" RDD design. Our main identifying assumption is that, in the absence of the program, the outcomes of unemployed workers would vary smoothly across the age threshold. Therefore, any observed discontinuities can be attributed to the effect of the job guarantee program. In the following, we discuss the assignment to treatment and the empirical approach in detail.

5.1 Treatment and assignment variable

Our treatment is defined by participation in the AK20 program, a variable that can be measured without error. The assignment underlying our RDD approach is based on the eligibility criteria, which we also observe perfectly in our data. While official eligibility was determined by both age and long-term unemployment, the latter criterion was disregarded by AMS in approximately 12% of cases (see Section 2). Therefore, for our empirical analysis, we rely solely on the age criterion. Eligible participants were those aged 50 years or older.

5.2 Econometric model

To address the issue of endogenous program participation, we use eligibility status as an instrumental variable (IV) for the endogenous treatment variable, actual participation in the AK20 program. In other words, we exploit the age-based cutoff in eligibility for the AK20 program. This leads to a fuzzy RDD, which we estimate using the two-stage least squares (2SLS) model, leveraging a sharp age-based discontinuity in eligibility. In the first-stage equation (1), we regress our endogenous treatment variable, $AK20_i$, indicating program participation of individual i, on their eligibility status, $eligible_i$:

$$AK20_i = \alpha_0 + \alpha_1 eligible_i + f(age_i) + \varepsilon_i, \tag{1}$$

where the running variable age enters as a linear function in the baseline model and the error term is denoted by ε_i. In the second-stage equation (2), we regress different labor market outcomes at relative time t, $Y_i^{(t)}$, on predicted $AK20$ participation ($\widehat{AK20}_i$) from equation (1):

$$Y_i^{(t)} = \beta_0^{(t)} + \beta_1^{(t)} \widehat{AK20}_i + f(age_i) + \xi_i^{(t)}, \qquad \forall t \in [-12, 48]. \tag{2}$$

Our main outcome of interest is a dummy variable that takes the value one if an individual is employed (including both subsidized as well as non-subsidized employment), and zero otherwise. We also consider a number of health outcomes and other employment and non-employment outcomes. We estimate this model separately for different relative time periods, $t = -12, -11, \ldots, 47, 48$. Our focus is on the parameters $\beta_1^{(t)}$, which represent the local average treatment effect (LATE) for relative time period t and provides the causal effect of the job guarantee program by being eligible for the program.

We will also present graphical results of the reduced form, which is a regression of the outcome of interest, Y_{it}, on the assignment variable $eligible_i$.

$$Y_i^{(t)} = \gamma_0^{(t)} + \gamma_1^{(t)} eligible_i + f(age_i) + \nu_{it}, \qquad \forall t \in [-12, 48], \tag{3}$$

which gives us the intention-to-treat (ITT) effects.

5.3 Identifying assumptions and balancing checks

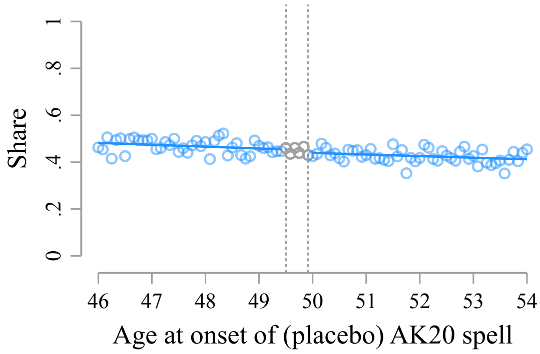
We have to impose three identifying assumptions. First, assignment to AK20 program participation must predict actual participation. Second, individuals must not precisely manipulate their eligibility criteria. Third, assignment must not be correlated with any outcome-determining factor.

The first condition is testable. Our first-stage regression shows an $\hat{\alpha}_1$ coefficient of 0.075, implying that assignment increases program participation by 7.53 percentage points. The estimated coefficient is highly statistically significant with an F-statistic of 215.22. This coefficient is stable across subsamples.

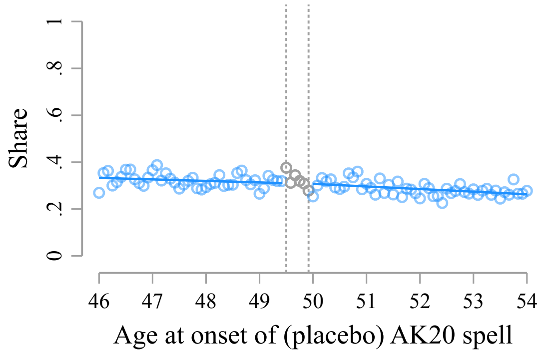
The inability to precisely manipulate treatment assignment is the key identifying assumption underlying any RDD. In our estimation approach, we exploit age-based eligibility as the assignment variable. Age is particularly suitable because it is, by definition, immutable. Furthermore, in our specific setting, we do not need to worry about individuals "aging into treatment," due to the abrupt suspension of the program after only half a year since we can simply exclude individuals who were between 49.5 and 50 years of age on July 1, 2017, akin to a "donut-hole" RDD design (Barreca et al., 2011). These individuals would have become eligible six months later, had the program not been suspended, and may have prepared in anticipation of a potential program start. Figure A.2 presents the number of observations by age around the eligibility cut-off and confirms that there is no evidence of manipulation or sorting around the cut-off. Whether assignment is correlated with any outcome-determining factor is not fully testable. However, we can investigate whether other observable characteristics of unemployed workers exhibit discontinuities at the age threshold. Figure 3 plots the means for each age bin (represented by blue circles) for the average share of females, the average share of individuals with a high school degree or higher, the average number of prior days of employment and the average number of prior days of unemployment in the last 15 years among individuals between 46 and 54 years of age. The dashed vertical lines indicate the 6-month window we exclude (represented by gray circles). The second dashed vertical line represents the age at which workers become eligible to participate in the AK20 program (50 years old). We observe no discontinuous jump in gender or in the proportion of individuals with at least a high school degree. Moreover, eligible and non-eligible individuals exhibit very similar trends in employment and unemployment durations. These insights are confirmed by regression-based analyses. First, we regress each (pre-determined) observable characteristic on AK20 participation, instrumented by eligibility. As expected, all estimated coefficients are statistically insignificant (see Appendix Table A.2).

In sum, we conclude that both observable characteristics and predicted outcomes vary

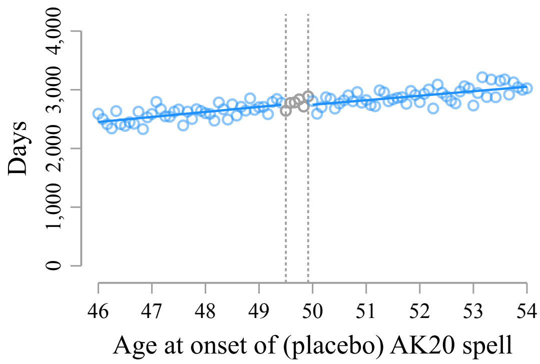
Figure 3: Discontinuity of socioeconomic and (prior) labor market characteristics.



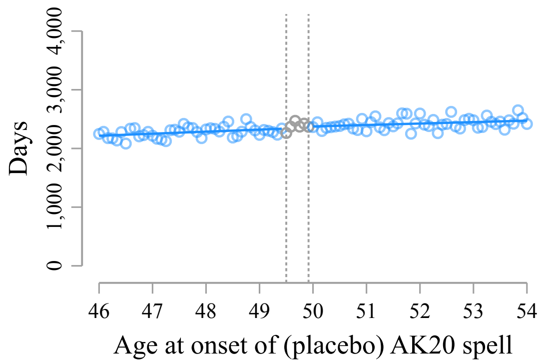
(a) Female



(b) High school degree or higher



(c) Prior days employed



(d) Prior days unemployed

Notes: Scatter plots represent the means for each age bin for the following outcome variables. Figures 3a and 3b present the means of indicator variables, which are equal to one for workers who are female or have a university degree, and zero otherwise. Figures 3c and 3d show binned means of prior days employed and prior days unemployed (prior days employed and unemployed are measured leading up to the (placebo) AK20 spell). The dashed vertical lines indicate the 6-month window we exclude in our main analysis (represented by gray circles). The second dashed vertical line represents the age at which workers are eligible to participate in the AK20 program (50 years old).

smoothly across the age threshold, supporting the validity of our identification strategy. A further strength of our research design is that non-compliance is one-sided. Individuals below age 50 — the eligibility cutoff in our IV framework — are mechanically excluded from participation in AK20. This rules out always-takers and defiers, leaving only compliers and never-takers. As a result, the monotonicity assumption is guaranteed by institutional design, and the IV estimates admit a clear interpretation as local average treatment effects for marginally eligible individuals.

6 Estimation results

In this section, we present our estimation results. First, we examine the causal effect of AK20 on our main outcome — employment — at different points in time. Second, we discuss the robustness of the results, considering changes in covariates, the estimation sample, variation in the bandwidth, and an alternative estimation method. Third, we present heterogeneous responses based on participant characteristics. Fourth, we investigate the mechanisms behind AK20's effectiveness in reintegrating older workers beyond the program's duration. We show which types of employment it fosters, which forms of non-employment it prevents, and highlight the types of firms in which successful participants find employment. Fifth, we examine potential spillover effects of the job guarantee program on non-participants including family members. In a final step, we assess the program's impact on health outcomes.

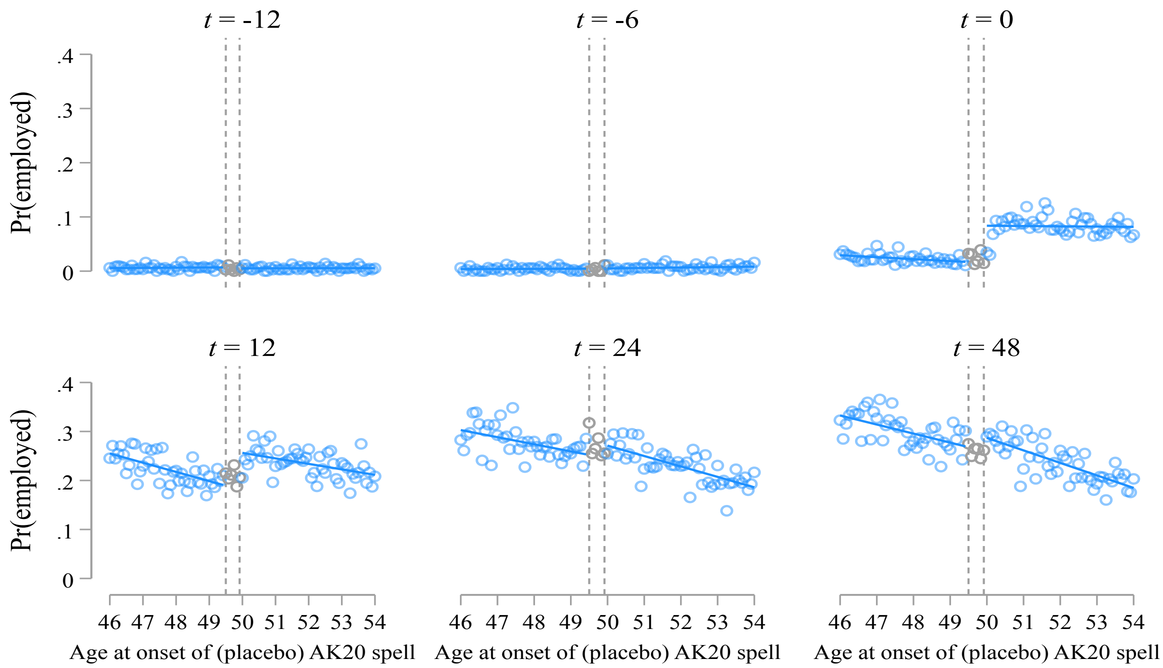
6.1 Effects on employment

We start by investigating the reduced-form relationship between assignment to treatment and employment based on equation (3). Figure 4 shows ITTs for different points in time relative to the start of the (placebo) AK20 spell.[19] Due to the construction of the dataset, we observe zero employment (effects) prior to the start of the AK20 program at $t = -12$ and $t = -6$. Once the program begins, the probability of employment increases discontinuously at the eligibility threshold. The positive impact on employment probability for eligible individuals is evident immediately at program start. While the effect is strongest at $t = 0$ and after one year ($t = 12$), the discontinuity in employment probability at the eligibility threshold remains persistent two and four years after the (placebo) start of AK20 participation. This indicates that eligibility for program participation is associated with an improved transition into the primary labor market.

In Table 2, we present our main estimation results based on the fuzzy RDD approach implemented via 2SLS. Program eligibility serves as a strong instrument, with a first-stage F-statistic of 215.22. Being eligible increases the probability of AK20 participation by

[19] Appendix Table A.3 provides equivalent regression-based results.

Figure 4: Intention-to-treat (ITT) effects of AK20 eligibility on employment



Notes: Scatter plots illustrate the mean probability of employment across age bins at various relative time points (relative to the start of the (placebo) AK20 spell). Linear fits are provided on both sides of the cut-off for better visualization. Dashed vertical lines highlight the six-month exclusion window (gray circles) which is omitted from the main estimation sample. The second dashed vertical line represents the age at which workers are eligible to participate in the AK20 program (50 years old).

Table 2: The impact of AK20 program participation on employment: 2SLS and OLS estimates

	Outcome variable is Pr(employed) at t					
t in months	-12	-6	0	12	24	48
Panel A: 2SLS						
AK20 participation	-0.024	0.002	0.880***	0.922***	0.404***	0.426***
	(0.025)	(0.023)	(0.058)	(0.130)	(0.141)	(0.143)
Panel B: OLS						
AK20 participation	-0.001	0.034***	0.682***	0.665***	0.218***	0.265***
	(0.002)	(0.005)	(0.012)	(0.010)	(0.013)	(0.013)
All						
Mean of dep. variable	0.01	0.01	0.06	0.23	0.25	0.26
Eligible						
Mean of dep. variable	0.01	0.01	0.08	0.23	0.23	0.24
Non-eligible						
Mean of dep. variable	0.01	0.00	0.02	0.22	0.28	0.30
Ad Panel A: First-stage coefficient on eligibility = 0.075***; F-Statistic = 215.22						

Notes: The dependent variable is a binary indicator for whether an individual is employed at time t, where t represents the number of months relative to the onset of the (placebo) AK20 spell. The endogenous treatment variable is a binary indicator for AK20 program participation. The number of observations in each estimation is equal to 31,797. Panel A presents 2SLS estimates, where actual AK20 participation is instrumented using program eligibility. Panel B provides OLS estimates for comparison, ignoring the endogeneity of AK20 program participation. The estimation sample includes individuals within a four-year age bandwidth on either side of the eligibility cut-off, excluding those whose ages fall within six months of the cut-off to minimize boundary effects. * p<0.10, ** p<0.05, *** p<0.01.

7.53 percentage points. Again, we present estimates at selected points in time relative to the onset of the (placebo) AK20 spell. In Panel A, we report 2SLS estimates, where actual AK20 participation is instrumented with program eligibility. In contrast, Panel B provides OLS estimates for comparison, ignoring potential endogeneity of AK20 participation. By construction, participants and non-participants are equally likely to be employed before the program starts (at $t = -12$ and $t = -6$). When the program begins at $t = 0$, participants are about 88 percentage points more likely to be employed. This effect remains nearly constant, rising to 92 percentage points one year later ($t = 12$). Importantly, the very high initial employment effects at $t = 0$ and $t = 12$ are primarily driven by employment within the program itself.

However, the impact of the program extends beyond its maximum duration of 24 months. AK20 participation helps treated workers reintegrate into the primary labor market. Two years after the program begins, participants are still significantly more likely to be employed, in fact by 40 percentage points. Four years after the program start — that is, at least two years after its conclusion — participants are 43 percentage points more likely to be employed, and even the lower bound of the 95 percent confidence interval (14.6 percentage points) represents a sizable and economically meaningful gain. The naïve OLS estimates are consistently lower. While AK20 participants are positively selected on observables (see Table 1) and Abowd, Kramarz, and Margolis (1999, AKM) fixed effects (see below), this does not imply that OLS must exceed the IV estimates. Our IV strategy identifies the local average treatment effect for individuals at the age cutoff (50), whereas OLS averages effects over all treated individuals aged 50–54. If treatment effects vary by age or attachment, the LATE at the cutoff can differ from the average OLS effect, even under positive selection.

Figure 5 provides a detailed visualization of our 2SLS estimates of $\beta_1^{(t)}$ from equation (2) for employment. Figure 5a presents estimates for each month t, ranging from one year before the (placebo) onset of the AK20 spell to 48 months afterward (blue dots). This illustrates the full adjustment path over time and enables a direct comparison of trends before and after the program's initiation. To highlight the role of actual participation in AK20, the gray shaded area shows the share of workers actively enrolled in the program over time. Figure 5b shows the program's impact on employment excluding AK20-subsidized jobs: here, employment spells subsidized by AK20 are coded as zero, and the resulting effects — estimated as in the upper panel — are shown as red squares.[20]

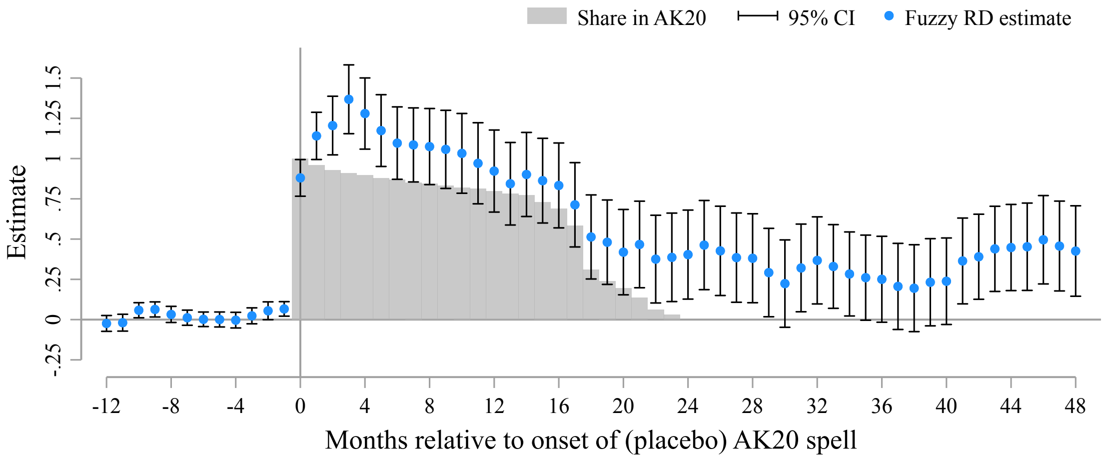
Focusing on the upper panel, we observe the key insights from Table 2, along with the full adjustment path based on monthly estimates over 48 months. Employment increases significantly for AK20 participants and remains elevated throughout the program's maximum duration of two years.[21] The middle panel illustrates the share of AK20 participants over time, showing that all participants have exited the program after 24 months. Most importantly, the lower panel demonstrates consistent and (mostly) statistically significant employment effects even beyond the program's maximum duration of 24 months. At least two years after the program's end, participants are still 43 percentage points more likely to be employed.

In sum, our main estimation results (summarized in Table 2 and Figure 5) clearly demonstrate that participation in the AK20 program enables older, long-term unemployed workers to re-enter the primary labor market and supports sustained employment, at least in the medium run.

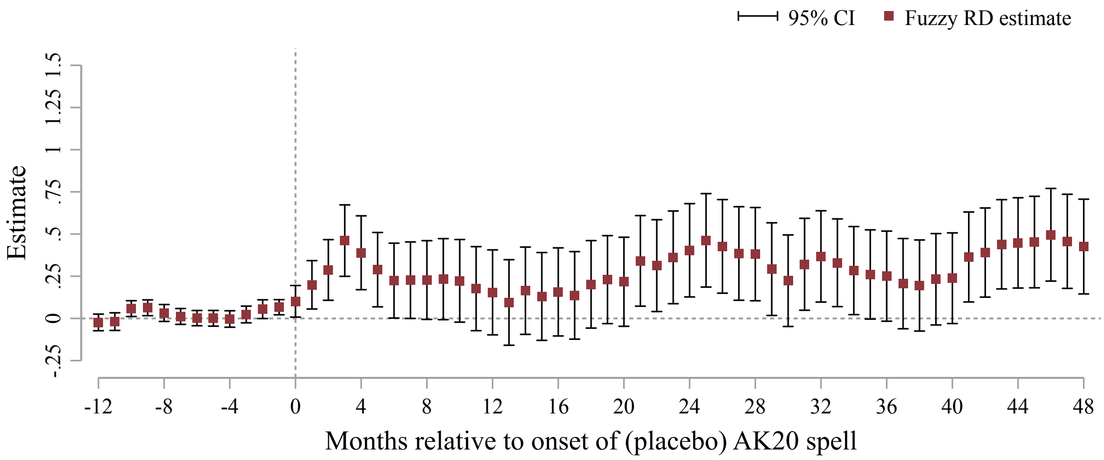
[20] Appendix Figures A.3a and A.3b provide equivalent OLS estimates.

[21] In the early program months, some predicted employment probabilities for treated individuals exceed one. This is a standard artifact of estimating a linear probability model via 2SLS when the treatment effect is very large and virtually all treated individuals are employed at the beginning of the program period. These values should therefore not be over-interpreted. For completeness, we also report 2SRI estimates below, which better accommodate the binary nature of the outcome variable.

Figure 5: The impact of AK20 program participation on employment: More detailed 2SLS estimates



(a) Total Employment



(b) Total Employment outside of the AK20

Notes: Figure 5 presents 2SLS estimates at various points in time relative to the onset of the (placebo) AK20 spell, where actual AK20 participation is instrumented using program eligibility. Figure 5a shows the probability of employment without imposing any restrictions on the outcome variable during the period of active program participation (blue dots). The gray shaded area displays the share of workers actively participating in the job guarantee program relative to all AK20 participants at each point in time. Figure 5b restricts the outcome variable to measure employment exclusively outside of the AK20 program (red squares). The number of observations in each estimation is equal to 31,797.

6.2 Robustness of employment result

We now assess the robustness of our main findings. First, we exclude AK20 participants who were not long-term unemployed prior to the program's start. As shown in Figure 1d, eligibility based on long-term unemployment prior to the first AK20 spell was not strictly enforced. Our empirical strategy therefore relies exclusively on assignment to the program based on age. When we exclude the 12% of AK20 participants who did not meet the long-term unemployment eligibility criterion, the resulting estimates remain highly comparable to our baseline results (see Panel A of Appendix Table A.4; compare with Table 2).

Second, we vary the placebo starting month of the treatment for non-participants. In our baseline, we assign July 2017 as the placebo start. However, the actual starting dates of participants vary over twelve months between July 2017 and June 2018. We test two alternative assignments: we assign placebo starting dates based on random draws from a uniform distribution over calendar months between July 2017 and June 2018, and we assign starting dates based on the empirical distribution of actual starting dates of AK20 participants (as summarized in Figure 1a). Our main results are robust to the choice of alternative placebo starting dates (see Panels B and C of Appendix Table A.4).

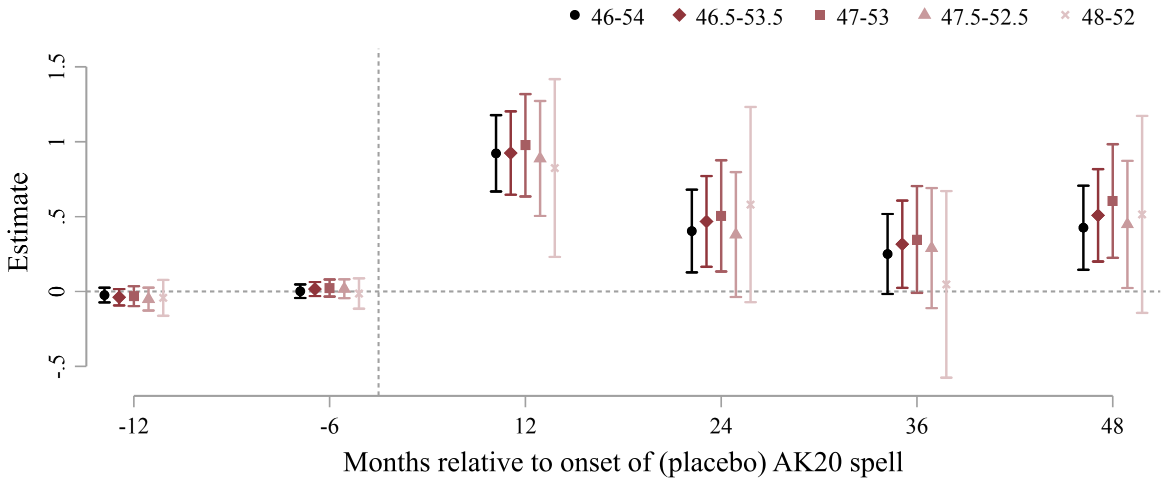
Third, we examine the sensitivity of our findings to the inclusion of additional covariates. Specifically, we include a vector of predetermined covariates capturing individuals' socioeconomic background and labor market history. The inclusion of these covariates has no substantive effect on our main estimates (see Panel D of Appendix Table A.4). This implies that assignment to the treatment is effectively random. In addition, our results are robust to the inclusion of a quadratic term in the running variable age. Lastly, the results are not sensitive to using separate trends of the running variable *age* on each side of the discontinuity (see the last row of Appendix Table A.4).

Fourth, we vary the bandwidth around the cutoff point. Figure 6 illustrates the impact of AK20 participation on employment at different points in time using alternative bandwidths.[22] Overall, the estimates show little sensitivity to the choice of bandwidth. All estimates indicate a higher probability of employment for AK20 participants, with effects remaining stable across all specifications up to four years after the program's start. As expected, narrower bandwidths with fewer observations lead to less precise estimates.

Fifth, we present estimates from an alternative estimation model. In our main analysis, we rely on a linear IV model to estimate the effect of AK20 participation on employment. However, the main outcome variables (being employed in t) are all binary indicators, which the linear IV model does not explicitly accommodate. Therefore, we also employ a two-stage residual inclusion (2SRI) approach, which explicitly accounts for the binary nature of the outcome variable (Terza, Basu, and Rathouz, 2008; Wooldridge, 2015). For the first stage, we rely on a linear regression as in equation (1). In contrast, the second

[22]Figure A.4 shows OLS estimates using alternative bandwidths.

Figure 6: 2SLS estimates with varying bandwidth



Notes: Figure 6 presents 2SLS estimates for the impact of program participation on employment for different time periods with varying window sizes. Dots show coefficients for the age window 46–54 (N = 31,797, N^{AK20} = 1,538, 1st stage F-statistic: 215.22), diamonds for 46.5–53.5 (N = 27,730, N^{AK20} = 1,337, 1st stage F-statistic: 181.06), squares for 47–53 (N = 23,456, N^{AK20} = 1,140, 1st stage F-statistic: 121.08), triangles for 47.5–52.5 (N = 19,354, N^{AK20} = 932, 1st stage F-statistic: 95.97), and × for 48–52 (N = 15,067, N^{AK20} = 748, 1st stage F-statistic: 39.29). In each estimation, we exclude individuals with ages within six months before the age cutoff.

Table 3: The impact of AK20 program participation on employment: 2SRI estimates

	Outcome variable is Pr(employed) at t					
t in months	-12	-6	0	12	24	48
Panel A: 2SRI non-transformed residuals						
AK20 participation	-0.016	-0.033	0.963***	0.776***	0.463***	0.475***
	(0.105)	(0.107)	(0.014)	(0.031)	(0.144)	(0.137)
Panel B: 2SRI transformed residuals						
AK20 participation	-0.053	-0.050	0.963***	0.802***	0.662***	0.647***
	(0.238)	(0.181)	(0.004)	(0.036)	(0.205)	(0.210)

Notes: The dependent variable is a binary indicator denoting whether an individual is employed at time t, where t refers to the number of months relative to the onset of the (placebo) AK20 spell. The number of observations in each estimation is equal to 31,797. Panel A reports 2SRI estimates using non-transformed residuals, while Panel B presents estimates incorporating transformed residuals. In the first stage, actual AK20 participation is regressed on program eligibility. In the second stage, the endogenous variable AK20 is included alongside the residual from the first stage and estimated using a logistic regression. The estimation sample includes individuals within a four-year age bandwidth on either side of the eligibility cut-off, excluding those whose ages fall within six months of the cut-off to minimize boundary effects * p<0.10, ** p<0.05, *** p<0.01.

stage (Equation 2) is estimated via logistic regression. Unlike the 2SLS approach, which substitutes the fitted values from the first stage, the 2SRI method uses a control function approach. It corrects for endogeneity by including the endogenous variable AK20 along with the residuals from the first stage in the second-stage regression.

Table 3 summarizes estimates incorporating the untransformed residual from the first stage (Panel A) and estimates including generalized residuals (Panel B), as proposed by Wooldridge (2015). The 2SRI estimates are closely aligned with our main results based on 2SLS (see Table 2).

6.3 Treatment effect heterogeneity

We now examine whether treatment effects vary across participants with different predetermined characteristics. Specifically, we investigate heterogeneities by sex, broad occupation, education, and unemployment history. The detailed estimation results are presented in Appendix Figure A.5. First, we find that treatment effects are very similar for men and women.

Second, we observe some heterogeneity across broad occupational categories. Workers are classified based on their last employment spell prior to AK20 participation. Blue-collar workers exhibit larger and more persistent employment effects that mirror our baseline pattern: the probability of employment is initially highest and remains positive even 48 months after program start. In contrast, white-collar workers experience an increase in employment only in the first months after entering the program, likely reflecting active participation. Because of their smaller sample size, estimates for white-collar workers are less precise, but they consistently indicate no meaningful longer-term employment effects. Overall, this suggests that the positive employment impacts are primarily driven by blue-collar workers.

Third, we distinguish participants by educational attainment, comparing those with compulsory schooling or apprenticeship training to those with at least a high school degree. We find no substantial differences across educational groups. Among highly educated participants, confidence intervals are somewhat wider, likely reflecting their smaller group size.

Fourth, we examine heterogeneity by labor market history, distinguishing individuals with above-median versus below-median prior days in unemployment. The results reveal no clear differences between these groups, suggesting that prior unemployment duration does not meaningfully influence the program's employment effects.

6.4 Potential mechanisms

We now turn to the mechanisms underlying AK20's effectiveness in facilitating the reintegration of older workers beyond the program period. To this end, we present empirical evidence on how and why the program generates sustained employment effects.

6.4.1 How did AK20 work?

Our main results show that AK20 participants are more likely to be employed. We now explore which specific types of employment AK20 fosters. It is important to establish whether the positive employment effects reflect regular, unsubsidized jobs or whether they arise from employment subsidized through other programs. The intensive margin is also relevant: we aim to assess whether employment is merely marginal or low-intensity, or whether it represents meaningful and sustained reintegration into the labor market.

Table 4: Days in labor market status after maximum program duration

	Outcome variable is *Days in*		
	(1)	(2)	(3)
	Total Emp.	Subsidized Emp.	Non-Subsidized Emp.
Panel A: Employment outcomes			
AK20 participation	254.451***	-2.194	256.070***
	(86.380)	(10.060)	(86.150)
	Outcome variable is *Days in*		
	(1)	(2)	(3)
	Unemployment	Retirement	Marginal Emp.
Panel B: Other employment and non-employment outcomes			
AK20 participation	−163.574*	−81.001**	−96.800**
	(98.014)	(36.174)	(48.793)

Notes: The dependent variable is the number of days after maximum program participation, i.e., between relative month 25 to 48 in (Panel A: 1) total employment, (Panel A: 2) subsidized employment, (Panel A: 3) non-subsidized employment, (Panel B: 1) unemployment, (Panel B: 2) retirement (regular, early, disability pension), and (Panel B: 3) marginal employment. Actual AK20 participation is instrumented using program eligibility. The estimation sample includes individuals within a four-year age bandwidth on either side of the eligibility cut-off, excluding those whose ages fall within six months of the cut-off to minimize boundary effects. The number of observations for each row corresponds to 31,797. * p<0.10, ** p<0.05, *** p<0.01.

Panels (a) and (b) of Figure 7 show that the initial increase in employment probability is driven primarily by gains in subsidized employment and, to a lesser extent, by non-subsidized employment.[23] However, the medium-term effect—after participants leave AK20—is entirely driven by increases in regular (i.e., non-subsidized) employment. A

[23]Subsidized employment comprises AK20 and any other subsidized employment spell.

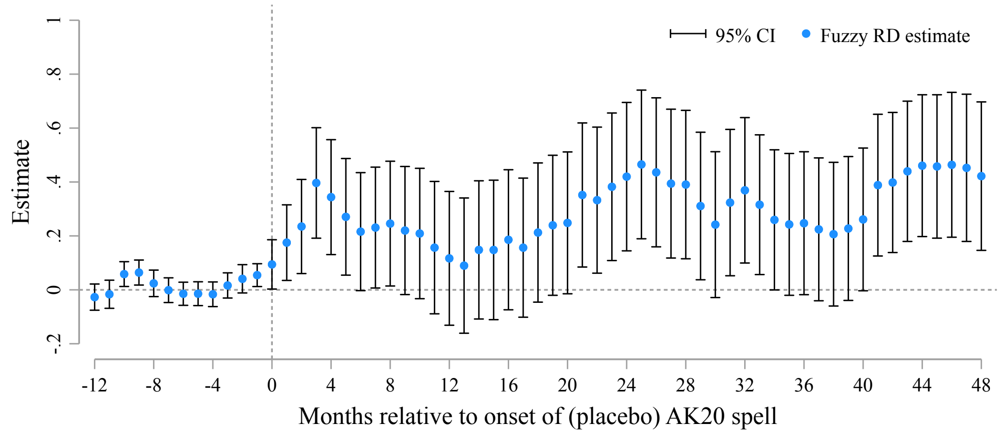
similar RDD analysis using the number of days in employment following the maximum program duration (i.e. in year 3 and 4) corroborates these findings. AK20 participants spent 255 additional days in employment during the two years after the program ended (see Table 4). This positive effect is fully accounted for by additional days in non-subsidized employment; we find no effect on days in subsidized employment. These results indicate that program participation facilitates a transition into the primary labor market once the program has concluded. Panel (c) of Figure 7 shows that the employment effects are not driven by marginal employment. On the contrary, we find a negative effect on marginal jobs, indicating that AK20 shifted participants away from low-intensity employment and toward more substantial labor market attachment. This effect is sizeable: over the two years following the maximum program duration, AK20 participants spent 97 fewer days in marginal employment (see Table 4). This suggests that the program does not merely push participants into any form of employment but facilitates full integration into the labor market. Thus, the quality of employment — not only its incidence — improves as a result of AK20 participation.

We now turn to which specific types of non-employment AK20 prevents. Figure 8 summarizes the effects of AK20 participation on unemployment, retirement, and out-of-labor-force status over time. Participants are less likely to be unemployed after the program begins, with the largest reductions occurring during the first two years—partly reflecting AK20-sponsored employment. In the subsequent two years, the unemployment effect diminishes somewhat. Given the relatively high age of AK20 participants, the program also has a substantial impact on (early) retirement, with the effect increasing as participants age. Our retirement measure encompasses regular retirement, early retirement, and disability pensions. Four years after program start, participants are 14 percentage points less likely to be retired than non-participants. Finally, we find no evidence that AK20 participation increases out-of-labor-force exits (see Panel c). Table 4 summarizes these effects over years 3 and 4 after programme start: participants spend 164 days less in unemployment and 81 days less in retirement.

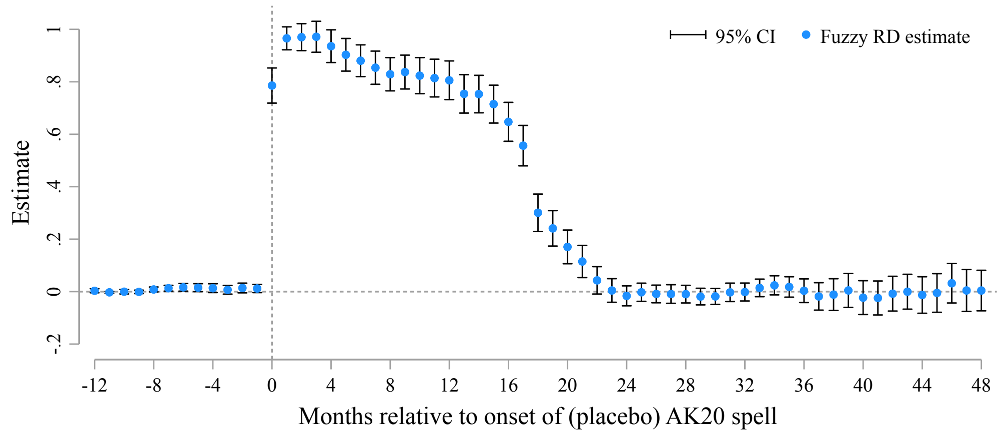
6.4.2 Why did AK20 work?

Several causal mechanisms may account for the success of AK20 in improving labor market outcomes among older long-term unemployed individuals. These mechanisms are closely connected to the literature on duration dependence in unemployment. Key mechanisms discussed in this literature include human capital depreciation during unemployment spells (Mincer and Ofek, 1982; Acemoglu, 1995; Albrecht et al., 1999), a decline in job search intensity over time (Krueger and Mueller, 2011; Faberman and Kudlyak, 2019), reduced job referrals from employment offices (Winter-Ebmer, 1990), employer discrimination against the long-term unemployed (see, for example, Oberholzer-Gee, 2008; Kroft, Lange, and Notowidigdo, 2013; Eriksson and Rooth, 2014), and declining employability due to

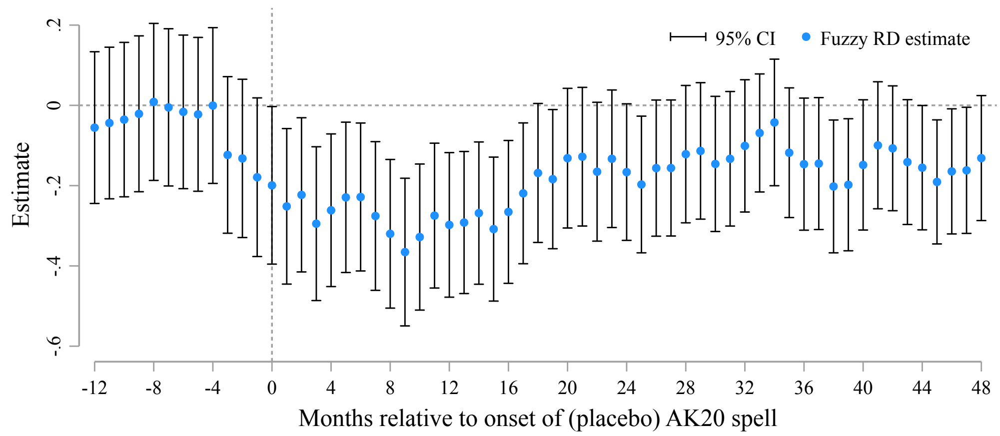
Figure 7: The effect of AK20 participation on different types of employment



(a) Non-subsidized employment



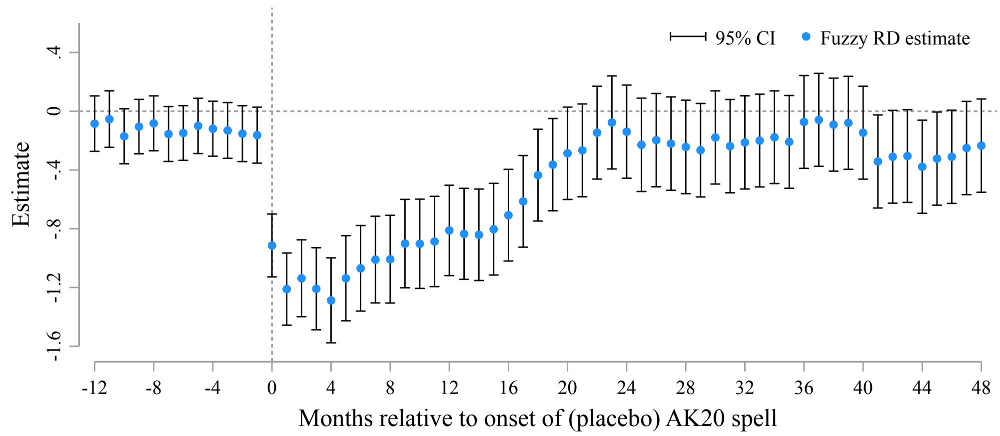
(b) Subsidized employment



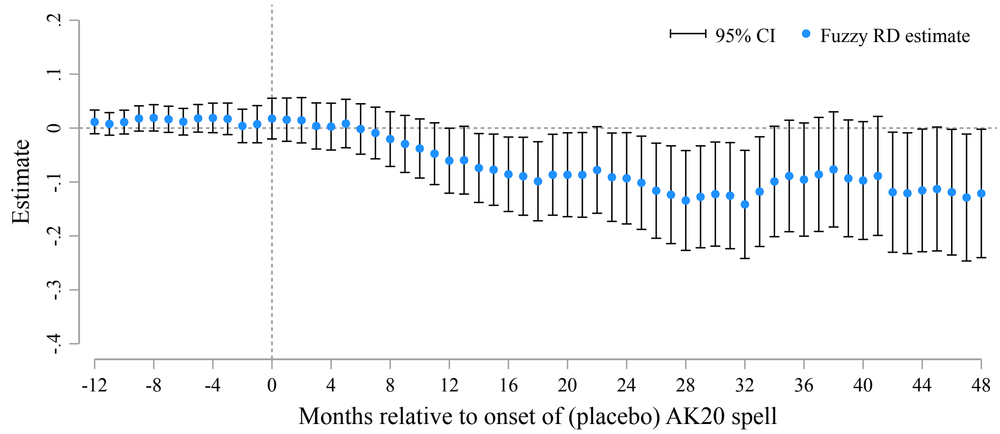
(c) Marginal employment

Notes: Figure 7 shows 2SLS estimates for different points in time relative to the onset of the (placebo) AK20 spell and for non-subsidized employment (7a), subsidized employment (7b), and marginal employment (7c). Actual AK20 participation is instrumented using program eligibility. The number of observations in each estimation is equal to 31,797.

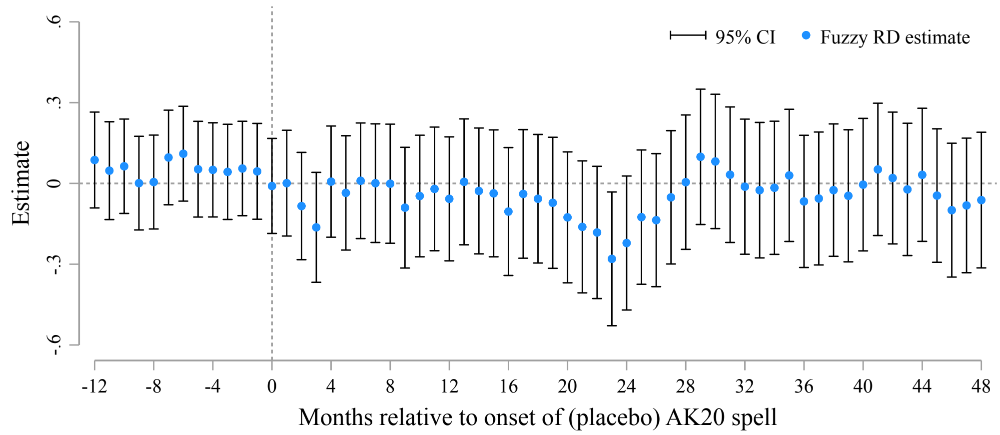
Figure 8: The effect of AK20 participation on different types of non-employment



(a) Unemployment



(b) Retirement (regular, early, DI)



(c) Out of labor force

Notes: Figure 8 shows 2SLS estimates for different points in time relative to the onset of the (placebo) AK20 spell and for the binary non-employment outcomes unemployment (8a), retirement (8b), and out of labor force (8c). Retirement includes regular retirement, early retirement, and disability pension. Actual AK20 participation is instrumented using program eligibility. The number of observations in each estimation is equal to 31,797.

the erosion of work habits or motivation (Koen, Klehe, and Van Vianen, 2013).

The success of AK20 is most likely driven by the fact that the program addresses *all* of these causal mechanisms simultaneously. In particular, AK20 participants benefited from a regular work schedule and actual employment, which not only provided on-the-job training but also enhanced their CVs by breaking the spell of long-term unemployment and reducing associated stigma. Because AK20 jobs appear as regular jobs on a CV, future employers are unlikely to distinguish them from unsubsidized employment, which likely reinforces the stigma-reducing effect. Additionally, the structure of the program — especially its clearly defined duration — may have encouraged participants to intensify their job search efforts during and after participation. While our research design does not allow us to separately identify the quantitative importance of the different mechanisms, we provide two additional analyses that offer suggestive evidence. First, we draw on subjective assessments from survey responses from a significant subset of AK20 participants. Second, we empirically describe the characteristics of successfully reintegrated workers and their subsequent job matches.

Survey evidence A total of 553 AK20 participants were interviewed via telephone using standardized questionnaires.[24] Survey evidence supports the interpretation that AK20 addressed several of these mechanisms. Many participants reported gains in professional competence and knowledge, underscoring the role of re-skilling and training—consistent with the idea that AK20 mitigated human capital depreciation. The program's structure, particularly its full-time schedule and defined duration, likely reactivated key aspects of employability such as reliability, routine, and work discipline. This is supported by survey responses indicating increased self-worth, a sense of appreciation, and improved problem-solving skills outside of work (Hausegger, Krüse, and Hager, 2019), in line with mechanisms related to the recovery of work habits and motivation. Only a small share of respondents viewed the program as a pathway to a permanent job with their AK20 employer, suggesting a realistic understanding of its temporary nature and a continued focus on job search. This supports the idea that AK20 helped sustain or revive job search intensity. By offering re-employment in a structured and socially recognized setting, the program may have helped to reduce the stigma of long-term unemployment. Respondents frequently noted improved self-confidence and saw participation as a valuable signal on their CVs — potentially mitigating employer discrimination.

Interestingly, more than half of the respondents (53%) reported that their AK20 job was roughly in line with their previous professional experience, while 48% indicated a mismatch. However, most of the latter group (67% of these 261 respondents) acknowledged that a career change was necessary to re-enter the labor market. This suggests that

[24]The survey respondents include 148 individuals who ended their program participation early (interviewed between October and November 2018) and 405 individuals who were still in the program (interviewed in April and May 2019). For details, see Hausegger, Krüse, and Hager (2019).

some AK20 participants had not been previously matched with suitable employers or job vacancies. AK20 may have helped address this mismatch by facilitating re-entry through alternative pathways.

Table 5: Characteristics of successful AK20 participants and their job matches

	Shares at j			
j in months relative to program exit	0	6	12	24
Panel A: Type of firm				
AK20 firm	0.64	0.54	0.49	0.43
Other subsidized firm	0.01	0.01	0.01	0.02
Regular firm	0.35	0.46	0.51	0.55
Panel B: Industry relative to AK20 firm: 2 digit				
Same industry	0.66	0.56	0.53	0.48
Other industry	0.34	0.44	0.47	0.51
No information	0.00	0.00	0.00	0.01
Panel C: Industry relative to last regular job: 2 digit				
Same industry	0.04	0.04	0.04	0.04
Other industry	0.96	0.96	0.96	0.96
No information	0.00	0.00	0.00	0.01
Panel D: Worker type based on AKM				
Low AKM worker fixed-effect	0.24	0.27	0.27	0.25
High AKM worker fixed-effect	0.74	0.71	0.71	0.73
No information	0.02	0.03	0.02	0.02
Panel E: Firm type based on AKM				
Low AKM firm fixed-effect	0.20	0.22	0.21	0.20
High AKM firm fixed-effect	0.76	0.73	0.74	0.74
No information	0.03	0.06	0.05	0.06
No. of observations	520	636	655	642

Notes: Table 5 shows the share of currently employed (non-subsidized) AK20 participants over time j relative to program exit. Panel A differentiates by type of firm. AK20 firm is the same firm in which the participant did the program, other subsidized firm is a firm in which the workers was previously in subsidzed employment (but not the AK20 firm), and regular firms are all other firms. Panel B presents shares of AK20 participants in an industry relative to the industry of the AK20 firm (2-digit NACE Rev 2. classification). Panel C shows shares of AK20 participants in an industry relative to the indutry of their last job before the program (2-digit NACE Rev 2. classification). Panel D differentiates between worker types based on AKM worker fixed effects, where high refers to those above average, and low to those below average. Panel E differentiates between firm types based on AKM firm fixed effects, where high refers to those above average, and low to those below average. The number of observations is the total number of AK20 participants in non-subsidized employment in period j relative to program exit.

Successful job matches We now aim to better understand the mechanisms at work by describing the characteristics of successfully reintegrated AK20 participants and their job matches. To this end, we follow individuals who transitioned into *non*-subsidized employment over time, relative to their exit from the program.[25] We characterize these successfully reintegrated workers in terms of their employers, the quality of their job match, and the type of employment obtained (see Table 5).

The literature on temporary jobs has linked positive long-term employment outcomes to the possibility of participants being directly hired by the same firm (Autor and Houseman, 2010). Twelve months after leaving the program, roughly half of successful AK20 participants in *non*-subsidized employment remain with the AK20 firm, while the other half transition to other firms (see Panel A in Table 5). A comparable share of successful participants not only left the AK20 firm but also switched to a different industry (defined at the 2-digit NACE level). Compared to the distribution across industries during the program, successful participants work to a lesser extent in human health and social work activities, administrative and support service activities, and other service activities. A higher proportion moved to firms operating in public administration, as well as education, and wholesale and retail trade (see column (3) in Appendix Table A.1). This suggests that job transitions typically occur across rather than within industries (see Panel B in Table 5). This pattern remains when we compare participants' post-AK20 industry to that of their last job in their most recent employment spell before joining the program.[26] The vast majority of successful AK20 participants in *non*-subsidized employment work in firms belonging to different industries than their pre-program job (see Panel C in Table 5). This is consistent with the survey evidence discussed above, which indicates that AK20 participants had not previously been well matched with suitable employers and that the program helped alleviate this mismatch.

Lastly, we can also characterize the workers who moved to *non*-subsidized employment based on their AKM fixed effects.[27] The majority of participants observed in *non*-subsidized employment after program exit are characterized by relatively high worker fixed effects—i.e., they earn higher wages than observably similar workers—which indicates that positively selected program participants tend to transition into *non*-subsidized employment (see Panel D in Table 5). When we focus on the characterization of firms, we find that above-average-paying firms (high firm fixed effects) disproportionately hire former AK20

[25] Note that the duration of program participation varies across individuals (as shown in Figure 1b), and we observe those who left the program early over a longer follow-up period.

[26] Note that we observe the firm's industry but not individuals' detailed occupations.

[27] We estimate the AKM model using a full worker-year panel from 1998 to 2018 that covers the entire Austrian labor force. Specifically, we estimate the wage equation $\log w_{it} = \boldsymbol{\delta}\mathbf{X}_{it} + \theta_i + \phi_{J(it)} + u_{it}$, where $\mathbf{X}_{it}$ comprises time-varying worker characteristics, θ_i denotes a worker fixed effect, and $\phi_{J(it)}$ is the fixed effect of firm J where worker i is employed in year t. From this model, we recover predictions for $\hat{\theta}_i$, which can be interpreted as time-invariant worker-level contributions to wages conditional on firm characteristics, and $\hat{\phi}_{J(it)}$, which are firm-wage components conditional on worker characteristics, and match those to our dataset.

participants (see Panel E in Table 5).

6.5 Indirect effects and spillovers

Having established the direct effects of AK20 on program participants, we now examine whether the intervention generated spillovers to non-treated individuals. Large-scale employment programs may displace non-participants in local labor markets or affect the labor supply decisions of household members. We therefore assess displacement effects in local labor markets and potential spillovers on family members.

6.5.1 Local labor market displacement

To assess whether AK20 displaced non-participants, we conduct a difference-in-differences (DiD) analysis using individual-level unemployment data and exploiting the staggered roll-out of the program. Specifically, we examine how regional exposure to AK20 participation affected the unemployment durations of non-participants in the short run in local labor markets.

The treatment group consists of the 25 pilot regions in which AK20 was initially rolled out, while the control group comprises the remaining 81 regions that were not exposed during the pilot phase.[28] We, therefore, focus on the short-run impact during the first six months following the initial roll-out in the pilot regions.

We define exposure to the program as the number of AK20 participants in a region relative to the stock of all unemployed individuals in that region at time t. This implies that treatment intensity is higher in regions with a larger share of AK20 participants, while control regions have zero exposure. Because the program was discontinued after only six months of enrollment, only a small share of eligible individuals entered the program: on average, 0.68% of the unemployed in treated regions were AK20 participants, with exposure ranging from 0 to 7.8%. Our objective is to examine how exposure to AK20 participants affected the unemployment durations of non-participants. Therefore, we estimate the following model:

$$\text{duration}_{irt} = \eta\,(\text{share}_r \times \text{post}_t) + \lambda_r + \psi_t + \omega_{irt} \tag{4}$$

where duration_{irt} denotes the number of days individual i in region r spends in unemployment at time t, and share_r is a continuous measure of treatment intensity, defined as the regional share of AK20 participants among all unemployed in July 2017. The variable post_t is an indicator equal to one in the post-treatment period (July 2017) and zero before. The model includes region fixed effects (λ_r) and period fixed effects (ψ_t), and standard

[28] Note that the distinction between pilot and control regions was not strictly adhered to in the later phase of the program.

errors are clustered at the regional level. We estimate this specification separately for different demographic subgroups.

We find no evidence that regions with higher AK20 participation experienced increases in unemployment duration among non-participants, indicating that the employment gains for program participants did not come at the expense of worsened labor market outcomes for others in the same regions (see Appendix Table A.5).

6.5.2 Family spillovers

Beyond potential displacement in the local labor market, program participation may also affect the labor supply of other household members. Employment programs can alter household income, time allocation, expectations about future earnings, or retirement decisions, and several studies document that shocks to one household member's labor market status can spill over to spouses or children. Motivated by this literature, we examine whether AK20 participation had indirect effects on the outcomes of partners and children. We identify spouses and children in the administrative records of the ASSD up to 2007.

The sample for partners is limited to individuals from our main sample whose spouse we can identify. It consists of 3,792 spouses of eligible individuals and 2,701 spouses of non-eligible individuals, with 362 spouses of AK20 participants (see Appendix Table A.6). While the sample looks very similar to the main estimation sample described in Table 1, we have reduced statistical power due to the reduced sample size. Spouses of AK20 participants have a slightly higher employment probability and a lower unemployment probability 12 months before the (placebo) start of the program compared to eligible and non-eligible individuals.[29] We estimate the model described in (2), where the outcomes of interest are binary indicators for the partner's labor market status.

For the sample of children, we define exposure to the program if one parent is an AK20 participant and eligibility if at least one parent is eligible.[30] The children estimation sample comprises 17,083 children of eligible individuals, 12,231 children of non-eligible individuals, and 1,426 children of AK20 participants (see Appendix Table A.7). Thus, we do not have a problem with reduced statistical power due to a smaller sample size. The characteristics of the parents (the subsample of actual AK20 participants and long-term unemployed individuals from our main sample), as well as the average number of children, are broadly comparable across eligible individuals, non-eligible individuals, and AK20 participants. Compared to our main estimation sample, this sample contains a larger share of female workers. Children of non-eligible workers have the lowest employment probability 12 months before the (placebo) start of the program, while unemployment probabilities

[29] We exclude two couples where both partners are AK20 participants.

[30] We exclude six children where both parents are AK20 participants. Since we also observe multiple children per parent, multiple children can be exposed to the same parent.

are similar across groups. We examine the impact of parental program participation on children's labor market outcomes and cluster standard errors at the family level to account for multiple children per parent.

For spouses, we find positive point estimates on employment outcomes, but we cannot reject that these effects are zero (see Appendix Figure A.6). However, we find a statistically significant negative effect on retirement, consistent with a joint-retirement channel (Zweimüller, Winter-Ebmer, and Falkinger, 1996): couples often coordinate retirement timing, so if AK20 reduces early retirement among participants, their spouses may also delay retirement to retire together. Although the effect is statistically significant, statistical power is limited, resulting in fairly wide confidence intervals; we therefore remain cautious in offering a precise quantitative interpretation. Nevertheless, it is a notable finding, as there is little existing evidence on positive intra-household labor-supply spillovers from ALMPs. Our results provide suggestive evidence that job-guarantee programs may stabilize entire households, not only the directly treated workers. In contrast, for children, we find no significant changes in employment or labor force participation (see Appendix Figure A.7). Overall, this suggests that AK20 can generate positive family spillovers—at least for spouses—by keeping them in the labor force somewhat longer.

6.6 Effects on health

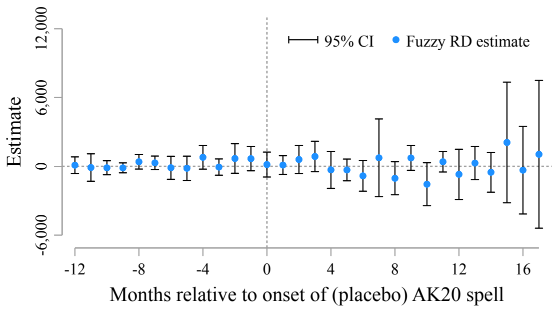
Austria operates a social health insurance system based on the Bismarck model, in which individuals are assigned to a statutory health insurance provider according to their employment status and occupation. Our data are sourced from the ÖGK, the main mandatory health insurance provider, which covers approximately 82% of the population – including the vast majority of employees and all non-employed residents. We have access to ÖGK data from the federal state of Upper Austria, covering the years 1998 to 2018 (see Section 3). Consequently, our estimation sample for analyzing health outcomes is smaller than the main sample introduced above, as it is limited to individuals residing (or working) in Upper Austria. It comprises 1,817 eligible individuals and 1,303 non-eligible individuals. Among the eligible group, 310 workers are AK20 participants (see Appendix Table A.8). AK20 participants exhibit similar average monthly health-care spending (per insured month) prior to treatment compared to both eligible and non-eligible individuals.

The ÖGK data allow us to observe healthcare utilization and prescription drug use before and after (placebo) program participation.[31] We use these data to examine the impact of program participation on total healthcare spending (in euros), as well as spending in the outpatient and inpatient sectors, and on prescription drugs.

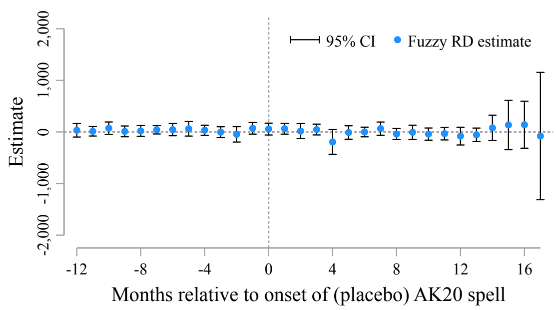
Figure 9 presents our 2SLS estimates of $\beta_1^{(t)}$ (see Equation 2) for five health outcomes. Prior to the start of the program, we observe no differences in healthcare spending between

[31] Note that we can observe health outcomes only up to the end of 2018 ($t = 17$), which does not extend beyond the program's maximum duration of 24 months.

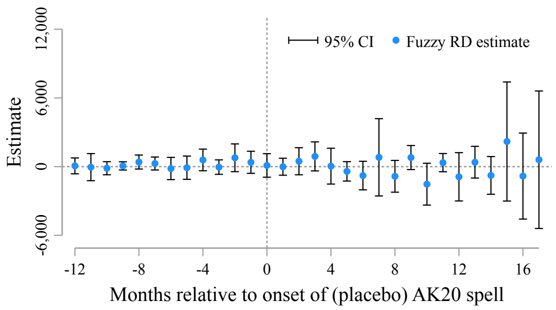
Figure 9: The effect of AK20 participation on health care utilization.



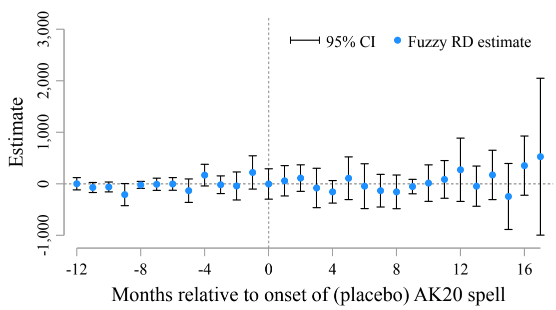
(a) Total health-care spending in Euro



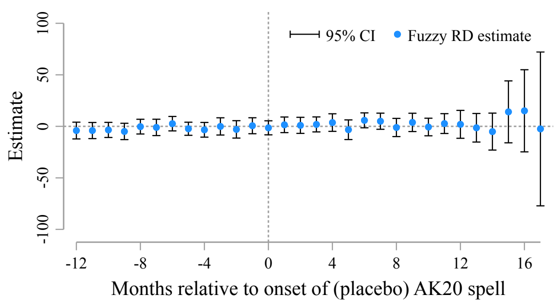
(b) Outpatient health-care spending in Euro



(c) Inpatient health-care spending in Euro



(d) Spending on prescription drugs in Euro



(e) Spending on antidepressants in Euro

Notes: Figure 9 shows 2SLS estimates for different points in time relative to the onset of the (placebo) AK20 spell and for total health-care spending in Euro (9a), outpatient health-care spending in Euro (9b), inpatient health-care spending in Euro (9c), spending on prescription drugs in Euro (9d), and spending on antidepressants in Euro (9e). Actual AK20 participation is instrumented using program eligibility.

AK20 participants and non-participants. Importantly, this is not a mechanical result, as our sample was not selected based on prior health status. This finding supports the validity of our research design, indicating that treated and control groups were comparable in terms of pre-treatment health expenditures.

Following program initiation, we detect no statistically significant or economically meaningful effects of AK20 participation on total healthcare spending over the 17-month observation period. This null result holds across all components of healthcare spending—namely, outpatient care, inpatient care, prescription drug and antidepressants expenditures. It remains possible that any potential health effects of program participation would only become visible over a longer time horizon.

7 Cost effectiveness

An important question for policymakers is whether the substantial investment in the AK20 program delivered value for money. In this section, we address this question in two steps. In Section 7.1, we examine whether the observed reintegration success required the maximum planned program duration of up to 24 months, or whether a shorter — and therefore less costly — exposure might have been sufficient. We begin with a simple comparison of employment outcomes across program participants with different realized program durations. We then exploit a mechanical feature of the program's implementation — namely that individuals who started the program from January 2018 onwards could participate for a maximum of 18 months due to the program's fixed termination date — to estimate the effect of marginal differences in program duration using an instrumental-variables approach that explicitly accounts for the endogeneity of realized time spent in the program.

In Section 7.2, we provide a simple approximation of the program's cost effectiveness by comparing the total costs of the intervention with its estimated economic benefits, including additional employment, increased tax revenues, and higher social security contributions.

7.1 Program duration

If one were to design an experiment on temporary job guarantees, a natural approach would involve treatment arms with varying program lengths. Such a design would allow researchers to determine the duration required to generate sustained employment effects in the primary labor market and to assess whether additional months of subsidized employment yield diminishing returns.

In the AK20 program, all participants were in principle eligible for a maximum program duration of up to two years. Unlike in a controlled experimental setting, however, realized program duration was not randomly assigned. Participants could exit the program early, for example after securing regular (i.e., non-subsidized) employment, or due to other individual circumstances and local labor market conditions. Figure 1b illustrates the share of participants who remained in the program over time. As a result, program duration is endogenous, and simple comparisons across participants with different durations do not admit a causal interpretation.

As a first step, we provide descriptive evidence on the relationship between program duration and subsequent employment outcomes. Specifically, restricting attention to actual

Table 6: The association between program duration and later employment

	Outcome variable is Pr(employed) at t		
t in months	12	24	48
6-10 months	-0.009	0.019	0.088
	(0.054)	(0.055)	(0.060)
11-15 months	0.527***	0.126**	0.120**
	(0.048)	(0.051)	(0.053)
16-20 months	0.765***	0.249***	0.243***
	(0.031)	(0.035)	(0.037)
21-24 months	0.762***	0.256***	0.294***
	(0.031)	(0.042)	(0.043)

Notes: The dependent variable is a binary indicator for whether an individual is employed at time t, where t represents the number of months relative to the onset of the (placebo) AK20 spell. The sample consists of actual AK20 participants aged 50-54 years old. The excluded category is a duration of one to five months in the program. The number of observations in each estimation is equal to 1,538. * p<0.10, ** p<0.05, *** p<0.01.

AK20 participants, we estimate regressions of the form

$$Y_i^{(t)} = \alpha + \sum_k \beta_k \mathbf{1}\{D_i \in k\} + \varepsilon_{it}, \tag{5}$$

where $Y_i^{(t)}$ is an indicator equal to one if individual i is employed t months after program start ($t \in \{12, 24, 48\}$) and D_i denotes realized program duration, grouped into five-month intervals. The omitted category consists of participants with a program duration of one to five months.

Table 6 summarizes the results. Compared with very short participation spells, longer program durations are associated with substantially higher employment probabilities at all horizons considered. The strongest associations are observed for individuals who participated for at least 16 months. Importantly, however, employment outcomes for the 16–20 month and 21–24 month duration brackets are very similar, suggesting diminishing returns to additional months beyond roughly one and a half years. While informative, these patterns should be interpreted with caution, as they may reflect selection rather than causal effects.

To address the endogeneity of realized program duration, we next exploit a mechanical feature of the program's implementation that generated exogenous variation in potential duration. All AK20 program spells were terminated in June 2019. As a consequence, participants who entered the program between July and December 2017 could in principle remain in subsidized employment for up to 24 months, whereas those who entered between January and June 2018 could remain for at most 18 months. We use this cohort-based variation in potential exposure as an instrument for realized program duration.

Formally, we estimate a two-stage least squares model. The first stage is given by

$$D_i = \pi_0 + \pi_1 Z_i + u_i, \tag{6}$$

where Z_i is an indicator for entering the program before January 2018, and thus having access to a longer maximum duration. The second stage relates employment outcomes to predicted program duration,

$$Y_i^{(t)} = \delta_0 + \delta_1 \widehat{D}_i + \eta_{it}. \tag{7}$$

The first stage is strong: participants who entered the program before January 2018 remained in the program, on average, 2.67 months longer than later entrants (first-stage F-statistic = 68.17; $F = 10.23$ when clustering standard errors at the program start-month level). In the second stage, we find that additional months of program participation induced by this variation do not measurably affect employment outcomes at 12, 24, or 48 months after program start. Estimated effects are small and statistically indistinguishable from zero, with wider confidence intervals when clustering at the start-month level.

Taken together, these results suggest that the reintegration gains documented above do not require the maximum planned program duration for the marginal participants affected by the program's early termination.

7.2 Back of the envelope cost-benefit calculation

To assess the cost effectiveness of the program, we proceed in three steps. First, we estimate the total program cost per participant. Second, we quantify employment benefits in terms of additional days worked in the primary labor market. Third, we compute an approximate balance of the program for the public finances. Appendix B reports the full arithmetic underlying this back-of-the-envelope calculation.

According to Walch and Dorofeenko (2020), the reduced-scale implementation of AK20 generated direct costs of 209 € million. These costs primarily reflect wage subsidies for the jobs provided and exclude potential additional expenditures related to central administration, such as counseling or case management. In total, 3,815 individuals participated in the program, implying an average direct cost of 54,784 € per participant.

Does AK20 pay for itself? To address this question, we conduct a rough calculation over the first four years after program start, focusing on fiscal savings resulting from higher tax revenues as well as lower unemployment benefit and pension payments. AK20 participation led to higher employment, fewer days of unemployment, and delayed entry into retirement. As shown in Table 4, participation increased employment by an average of 643 days during the first two years after program start and by an additional 254 days in years three and four.

Assuming annual earnings of 25,200 €, we approximate additional tax revenues of 1,125 € per year, yielding cumulative tax revenues of 4,500 € over the four-year period.[32]

Savings in unemployment benefit payments are calculated using an average benefit replacement rate of 55%. AK20 reduced unemployment by 578 days in the first two years and by 164 days in years three and four. This implies savings of 21,948 € in years one and two and 6,227 € in years three and four, yielding cumulative unemployment benefit savings of 28,176 €. Reduced pension payments arise only in years three and four, when AK20 participation lowers time spent in retirement by an average of 81 days. Valuing these days at a pension replacement rate of 80% yields estimated pension savings of 4,473 €.

Summing these components yields total fiscal benefits of approximately 37,149 € over the first four years, corresponding to about 68% of the program's direct costs. These calculations exclude administrative costs, which are difficult to quantify. While we do not estimate employment effects beyond year four, the average participant entered the program at age 54.6, suggesting that additional fiscal savings could plausibly accrue prior to retirement. One potential avenue for improving cost effectiveness would be to reduce the maximum program duration—for example, to 18 months instead of 24 months.

8 Conclusion

Older long-term unemployed workers are among the most difficult groups to reintegrate into the labor market. We study a temporary job guarantee program that offered up to two years of fully subsidized, meaningful work to this population. Using a sharp age-based discontinuity in eligibility, we show that the program substantially improved medium-term employment prospects

The effects are large and highly persistent. One year after entry, participants were 92 percentage points more likely to be employed, and even four years after the program began — that is, two years after its maximum duration ended — they remained 43 percentage points more likely to hold a job. These gains reflect genuine reintegration into the primary labor market rather than continued subsidized employment. Participants moved into regular, unsubsidized jobs, frequently at new employers and often in different industries, suggesting a meaningful improvement in employability and matching quality. They were less likely to retire early, to enter marginal employment, and they accumulated substantially fewer days of unemployment in the years after program exit.

Why did AK20 work? The program simultaneously addressed multiple sources of duration dependence — skill depreciation, stigma, loss of routine, declining search effort, and reduced referrals — by returning participants to structured, full-time work. Survey evidence points to improvements in self-confidence, motivation, and perceived signaling

[32]This calculation assumes constant annual earnings over the four-year window and abstracts from changes in the tax schedule.

value, which is consistent with our finding that participants transitioned into regular jobs at employers with no direct exposure to the program. The combination of work experience, renewed structure, and credible signaling appears central to the large and persistent impacts we document.

In our natural experiment, only about 5–10 percent of all potentially eligible individuals entered AK20, and we find no evidence of displacement or crowding-out effects. Labor market outcomes of non-participants in more exposed regions did not worsen, suggesting no substantial general equilibrium effects on the broader population. Within families, we find no significant spillovers on children, but we do observe a statistically significant negative effect on spousal retirement. This finding is notable, as active labor market policies rarely generate positive intra-household labor-supply spillovers. While the spousal retirement effect should be interpreted cautiously given the reduced statistical power of the spouse sample, it is consistent with well-documented joint retirement behavior in couples (see, for instance Zweimüller, Winter-Ebmer, and Falkinger, 1996; Blau, 1998b). Taken together, this evidence suggests that job guarantees may stabilize entire households, not only the directly treated workers. On the health side, we observe no meaningful short-run effects on healthcare utilization, although the window over which health outcomes can be observed is limited.

Taken together, our findings demonstrate that a carefully designed temporary job guarantee, emphasizing additionality, meaningful tasks, and minimal substitutability, can effectively reintegrate older long-term unemployed workers. Whether these effects would persist under a large-scale expansion remains an open question. We do not observe general equilibrium effects in our setting, but our experiment covers only a small subset of the roughly 74,000 individuals who would have been eligible in 2017. However, this eligible population constitutes a small share of all unemployed workers and an even smaller share of the labor force, making it plausible — though not guaranteed — that scaling would not depress wages, vacancy creation, or job-finding rates for other groups by a large extent.

The more binding constraint to expansion is likely administrative and organizational rather than macroeconomic: the supply of meaningful, suitable, and clearly non-substituting jobs that public and non-profit employers can create and supervise. Understanding how to design and scale such positions — while preserving additionality — remains a key challenge for future research and policy.

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Web appendix

This Web Appendix provides additional material discussed in the unpublished manuscript "Reintegrating Older Long-Term Unemployed Workers: The Impact of Temporary Job Guarantees" by Alexander Ahammer, Martin Halla, Pia Heckl, and Rudolf Winter-Ebmer.

A Additional figures and tables

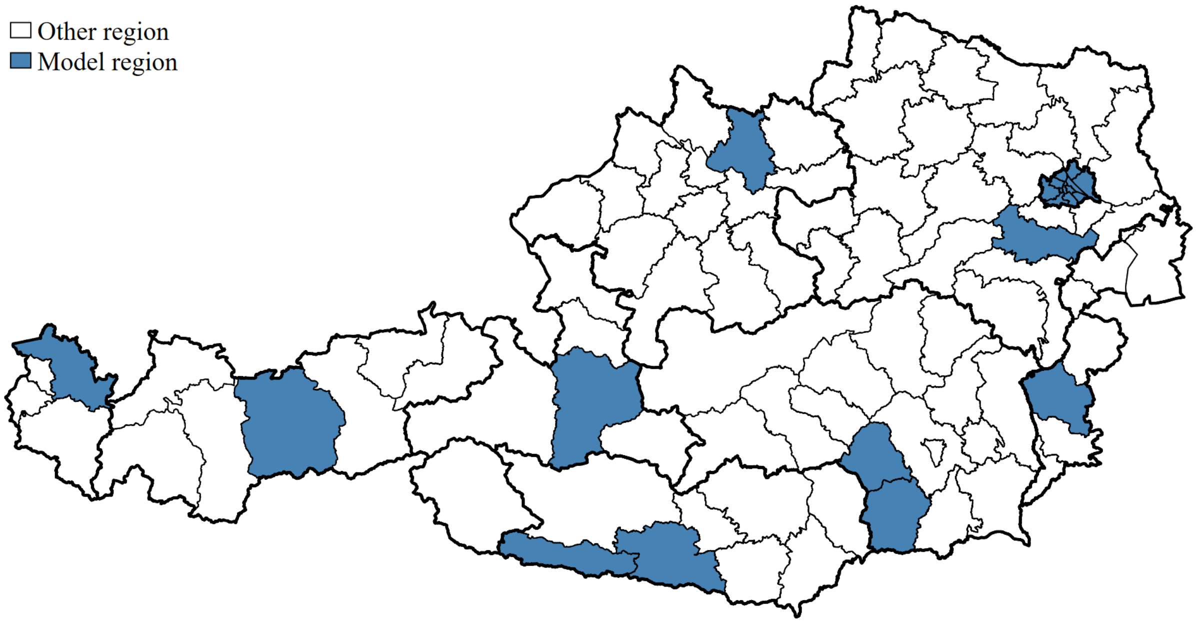
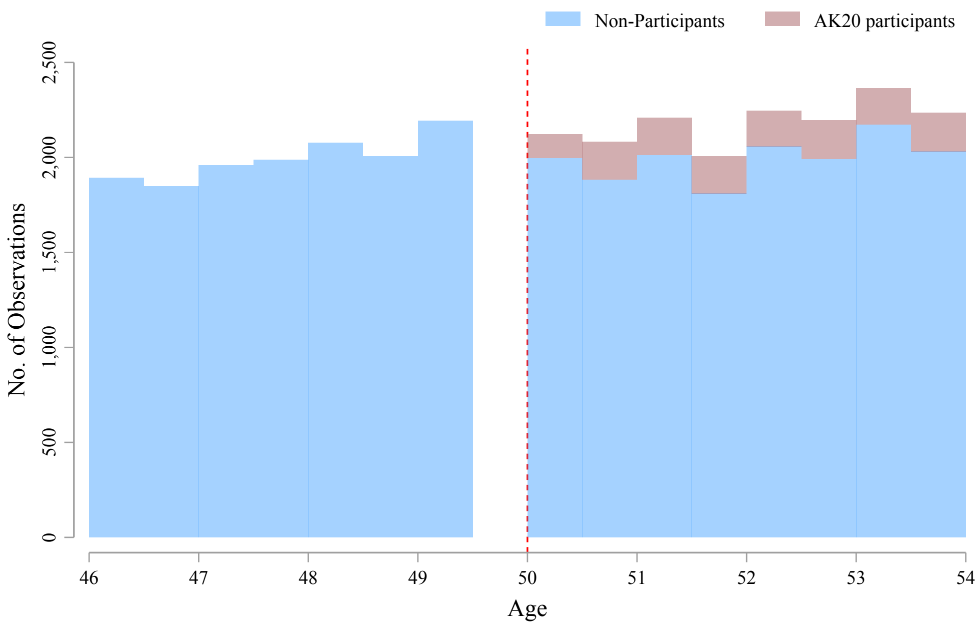


Figure A.1: Model regions

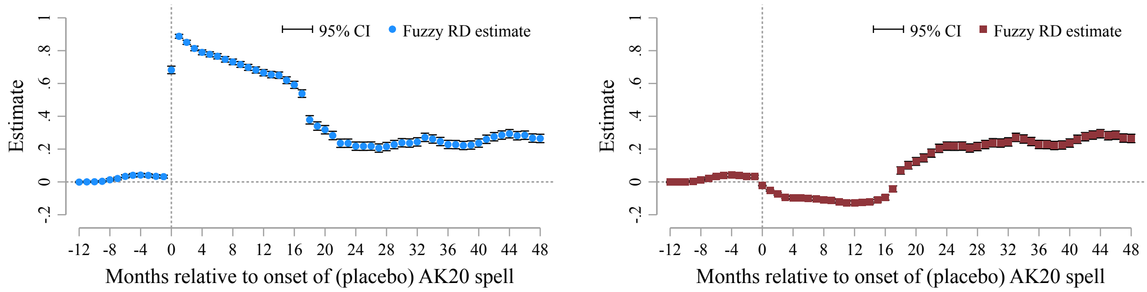
Notes: Figure A.1 shows model regions (dark blue) and non-model regions (white) across Austria.

Figure A.2: No. of observations



Notes: Figure A.2 shows the density of the number of observations around the eligibility cut-off (50 years old). We exclude individuals with ages within six months before the age cutoff. Blue bars show non-participants and red bars AK20 participants.

Figure A.3: The effect of AK20 participation on employment

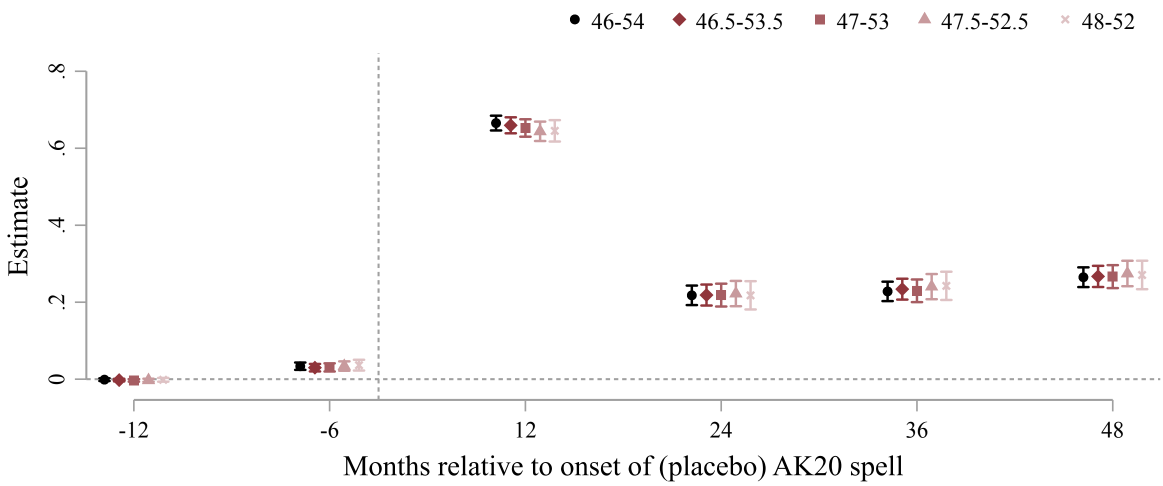


(a) Employment

(b) Employment outside of the AK20

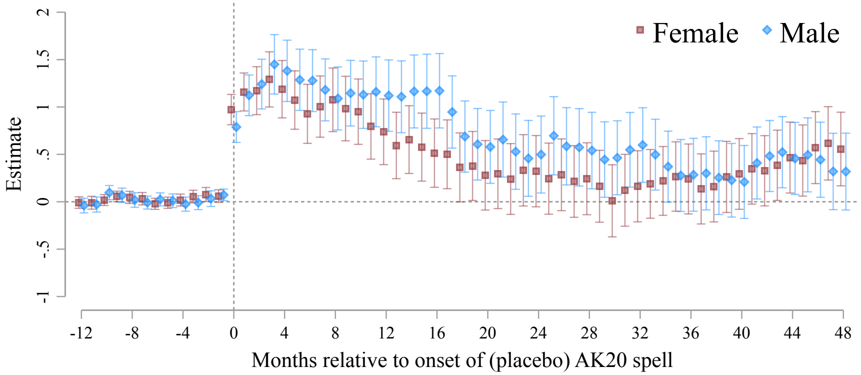
Notes: The dependent variable is a binary indicator for whether an individual is employed at time t, where t represents the number of months relative to the onset of the (placebo) AK20 spell. This figure presents OLS estimates at various points in relative time t, where the outcome variable is regressed on AK20 program participation. The left panel (A.3a) shows the probability of employment without imposing any restrictions on the outcome variable during the period of active program participation (blue dots). The right panel (A.3b) restricts the outcome variable to measure employment exclusively outside of the AK20 program (red squares). The number of observations in each estimation is equal to $31,797$. The estimation sample includes individuals within a four-year age bandwidth on either side of the eligibility cut-off, excluding those whose ages fall within six months of the cut-off to minimize boundary effects.

Figure A.4: OLS estimates with varying bandwidth

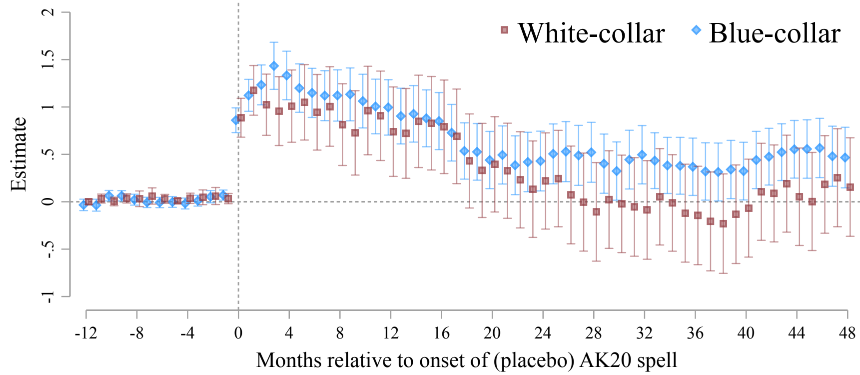


Notes: Figure A.4 presents OLS estimates for the impact of program participation on employment for different time periods with varying window sizes. Dots show coefficients for the age window 46–54 (N = 31,797, N^{AK20} = 1,538), diamonds for 46.5–53.5 (N = 27,730, N^{AK20} = 1,337), squares for 47–53 (N = 23,456, N^{AK20} = 1,140), triangles for 47.5–52.5 (N = 19,354, N^{AK20} = 932), and $\times$ for 48–52 (N = 15,067, N^{AK20} = 748). In each estimation, we exclude individuals with ages within six months before the age cutoff.

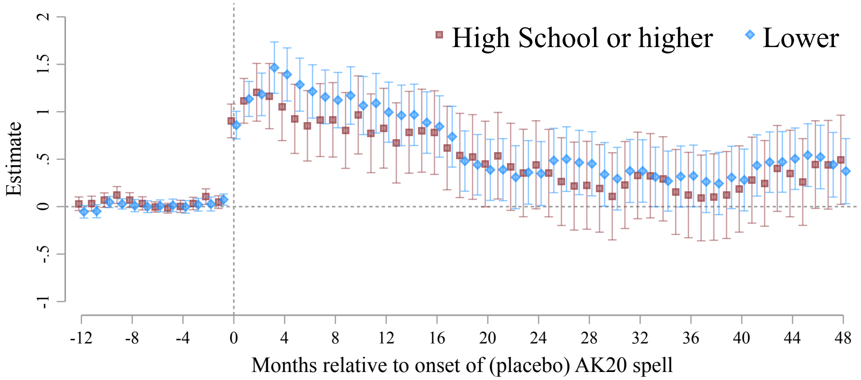
Figure A.5: The impact of AK20 program participation on employment: Treatment effect heterogeneity



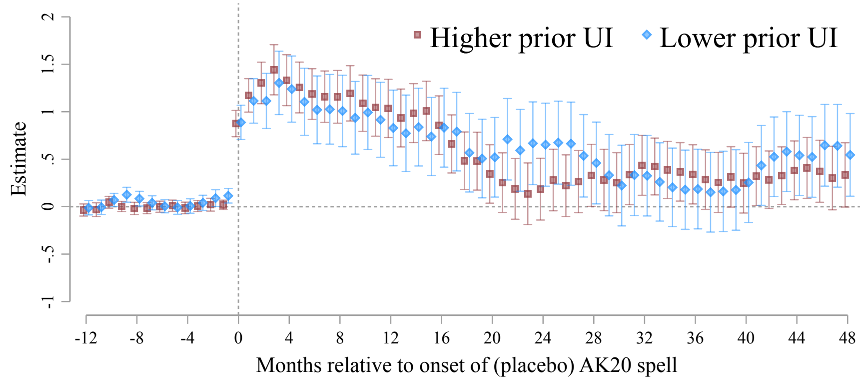
(a) Sex



(b) Blue-collar vs. white-collar



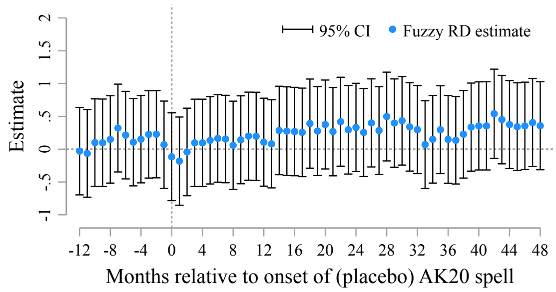
(c) Educational attainment



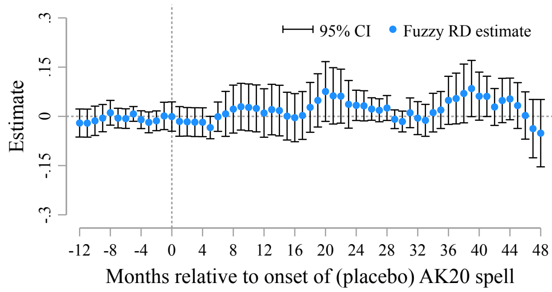
(d) Prior days in unemployment

Notes: Figure A.5 shows 2SLS estimates for different points in time relative to the onset of the (placebo) AK20 spell. Actual AK20 participation is instrumented using program eligibility. The figures show the probability of employment for different groups. Figure A.5a for female and male workers (N(female)= 14,121; N(male)=17,676), figure A.5b for blue- and white-collar workers (N(blue-collar)= 27,766; N(white-collar)=2,766), figure A.5c for individuals with at least a high school degree and those with compulsory school or an apprenticeship training (N(high school or higher)= 9,314; N(lower than high school)=21,705), and figure A.5d for individuals with below median prior days in unemployment ($UIdays < 2129$) and those with median and above prior days in unemployment (N(lower prior UI)= 15,771; N(higher prior UI)=16,026).

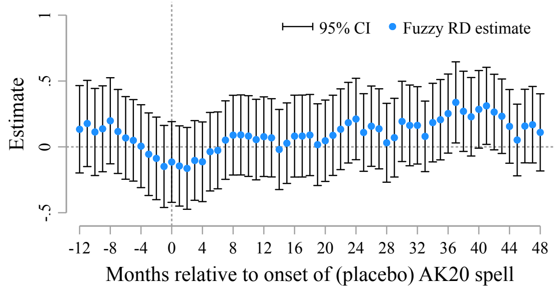
Figure A.6: The effect of AK20 participation on the outcomes of spouses



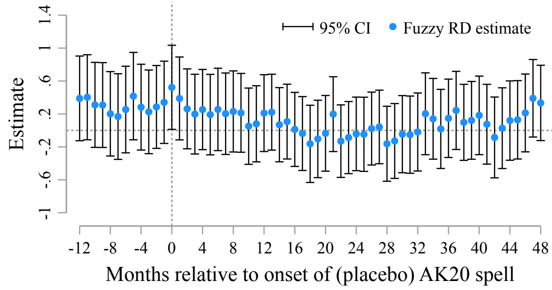
(a) Non-subsidized employment



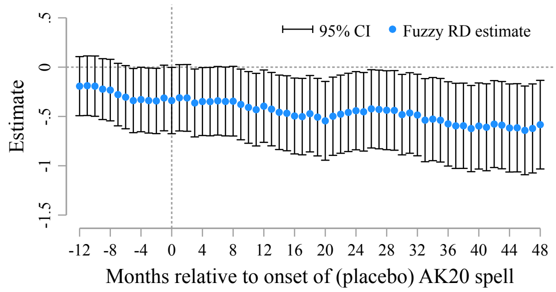
(b) Subsidized employment



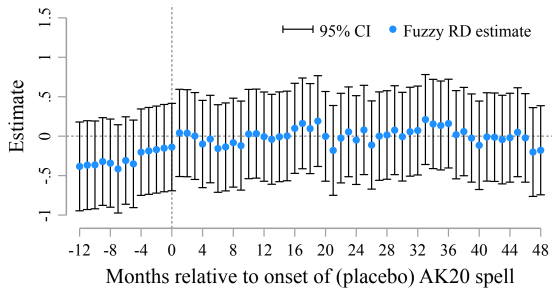
(c) Marginal employment



(d) Unemployment



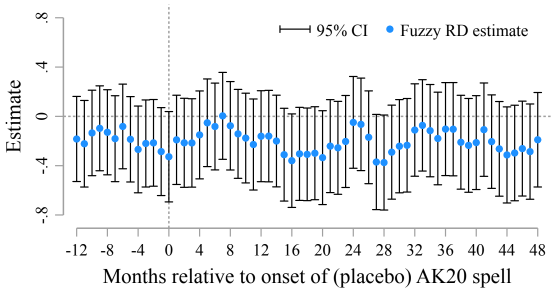
(e) Retirement (regular, early, DI)



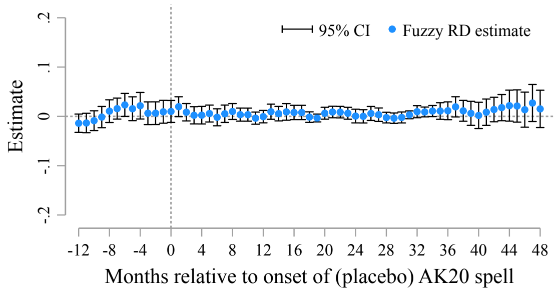
(f) Out of labor force

Notes: Figure A.6 shows 2SLS estimates for different points in time relative to the onset of the (placebo) AK20 spell and for spouses of AK20 participants. Each panel corresponds to the following labor market outcomes of spouses: (a) non-subsidized employment, (b) subsidized employment, (c) marginal employment, (d) unemployment, (e) retirement (early, regular, DI), and (f) out of the labor force. Actual AK20 participation is instrumented using program eligibility. The number of observations in each estimation is equal to 6,493.

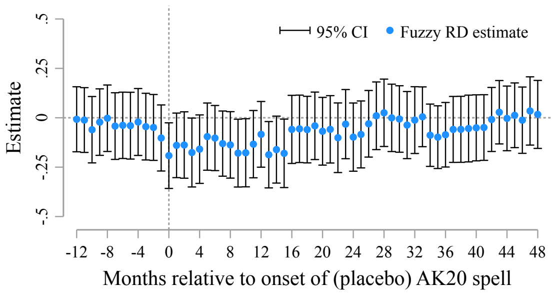
Figure A.7: The effect of AK20 participation on the outcomes of children



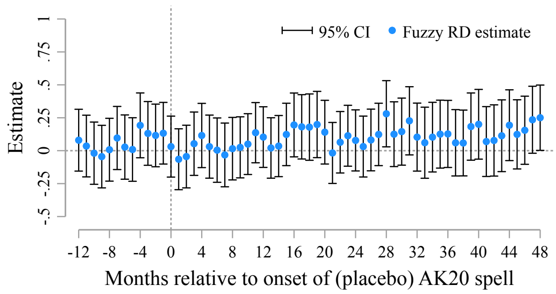
(a) Non-subsidized employment



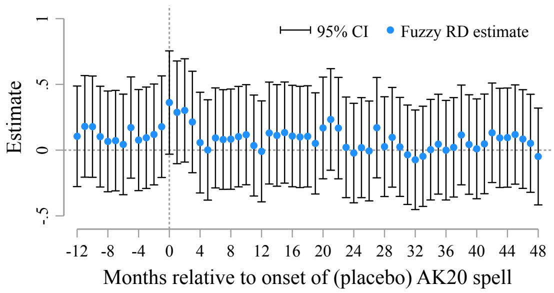
(b) Subsidized employment



(c) Marginal employment



(d) Unemployment



(e) Out of labor force

Notes: Figure A.7 shows 2SLS estimates for different points in time relative to the onset of the (placebo) AK20 spell and for children of AK20 participants. Each panel corresponds to the following labor market outcomes of children: (a) non-subsidized employment, (b) subsidized employment, (c) marginal employment, (d) unemployment, and (e) out of the labor force. Actual AK20 participation is instrumented using program eligibility. Standard errors are clustered at the family level. The number of observations in each estimation is equal to 29,314.

Table A.1: Industries of AK20 firms

	Share of AK20 participants		
	(1) *All* $t = 0$	(2) *Main Sample* $t = 0$	(3) *Successful* $j = 24$
Human Health and Social Work Activities	46.40	47.72	31.00
Public Administration&Defence; Social Security	23.15	23.60	33.64
Administrative and Support Service Activities	13.00	12.42	7.01
Other Service Activities	9.20	8.13	2.65
Arts, Entertainment, and Recreation	2.18	1.89	1.56
Education	1.76	1.89	3.89
Professional, Scientific, and Technical Activities	1.36	1.50	3.12
Manufacturing	0.94	0.85	2.18
Real Estate Activities	0.39	0.39	0.93
Accommodation and Food Service Activities	0.37	0.39	2.02
Water Supply; Sewerage, Waste Management	0.31	0.13	0.93
Wholesale and Retail Trade; Motorcycles	0.29	0.46	4.83
Construction	0.21	0.07	2.49
Transportation and Storage	0.13	0.20	1.40
Information and Communication	0.13	0.13	0.93
Electricity, Gas, Steam, Air Conditioning Supply	0.08	0.13	0.31
No. of observations	3,815	1,538	642

Notes: This table describes the industries of AK20 firms (NACE Rev. 2) for (1) all AK20 participants at $t = 0$ relative to the onset of the AK20 spell; (2) AK20 participants in the main sample (aged 46–54) at $t = 0$ relative to the onset of the AK20 spell; and (3) successful AK20 participants from our main sample (aged 46–54) employed (non-subsidized) at $j = 24$ months after program exit.

Table A.2: Selection on observables

	Outcome variable		
	(1)	(2)	(3)
	Pr(female)	Pr(blue-collar)	Pr(high education)
2SLS			
AK20 participation	-0.155	0.089	0.056
	(0.162)	(0.094)	(0.147)
Mean. of dep. variable	0.44	0.91	0.30
	Outcome variable		
	(4)	(5)	(6)
	Pr(model region)	Prev. UI Days	Prev. employed days
2SLS			
AK20 participation	-0.033	377.317	-587.383
	(0.161)	(498.066)	(635.166)
Mean. of dep. variable	0.55	2,359.37	2,770.73

Notes: The dependent variable is (1) a binary indicator for being female, (2) being a blue-collar worker, (3) having high school or above education, (4) being in a model region, and the prior days in unemployment (5) and employment (6). Actual AK20 participation is instrumented using program eligibility. The estimation sample includes individuals within a four-year age bandwidth on either side of the eligibility cut-off, excluding those whose ages fall within six months of the cut-off to minimize boundary effects. The number of observations is 31,797 for column (1), 30,295 for column (2), 31,019 for column (3), 31,797 for column (4), 31,491 for column (5) and (6). * p<0.10, ** p<0.05, *** p<0.01.

Table A.3: The impact of eligibility on employment: Intention-to-treat effects

	Outcome variable is Pr(employed) at t					
t in months	-12	-6	0	12	24	48
Eligible	-0.002	0.000	0.066***	0.069***	0.030***	0.032***
	(0.002)	(0.002)	(0.005)	(0.009)	(0.010)	(0.010)
Mean of dep. variable	0.01	0.01	0.06	0.23	0.25	0.26

Notes: The dependent variable is a binary indicator for whether an individual is employed at time t, where t represents the number of months relative to the onset of the (placebo) AK20 spell. The outcome variable is regressed on the assignment variable indicating eligibility as described in equation 3. The number of observations in each estimation is equal to 31,797. The estimation sample includes individuals within a four-year age bandwidth on either side of the eligibility cut-off, excluding those whose ages fall within six months of the cut-off to minimize boundary effects. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4: The impact of AK20 program participation on employment: 2SLS estimates, robustness

	Outcome variable is Pr(employed) at t					
t in months	-12	-6	0	12	24	48
Panel A: Excluding AK20 participants w/o LTU						
AK20 participation	-0.025	-0.021	0.916***	0.965***	0.422***	0.444***
	(0.028)	(0.022)	(0.063)	(0.142)	(0.154)	(0.157)
Panel B: Start date following empirical distribution						
AK20 participation	-0.004	0.112**	1.019***	0.796***	0.304**	0.412***
	(0.022)	(0.050)	(0.113)	(0.132)	(0.139)	(0.144)
Panel C: Including covariates						
C1. AK20 participation	-0.025	0.004	0.876***	0.941***	0.387***	0.422***
	(0.025)	(0.023)	(0.058)	(0.128)	(0.139)	(0.141)
Socioeconomic background	Yes	Yes	Yes	Yes	Yes	Yes
C2. AK20 participation	-0.027	-0.001	0.866***	0.984***	0.434***	0.448***
	(0.025)	(0.023)	(0.058)	(0.127)	(0.135)	(0.137)
Socioeconomic background	Yes	Yes	Yes	Yes	Yes	Yes
Labor market history	Yes	Yes	Yes	Yes	Yes	Yes
C3. AK20 participation	-0.025	0.005	0.878***	0.956***	0.364**	0.385***
	(0.026)	(0.022)	(0.055)	(0.133)	(0.144)	(0.146)
Age^2	Yes	Yes	Yes	Yes	Yes	Yes
C4. AK20 participation	-0.026	0.007	0.879***	0.956***	0.336**	0.352**
	(0.026)	(0.022)	(0.054)	(0.133)	(0.144)	(0.146)
Separate trends	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is a binary indicator for whether an individual is employed at time t, where t represents the number of months relative to the onset of the (placebo) AK20 spell. The endogenous treatment variable is a binary indicator for AK20 program participation. The table lists second stage 2SLS estimates, where actual AK20 participation is instrumented using program eligibility. The estimation sample includes individuals within a four-year age bandwidth on either side of the eligibility cut-off, excluding those whose ages fall within six months of the cut-off to minimize boundary effects. Panel A is based on an estimation sample excluding AK20 participants that were not long-term unemployed prior to the start of the program (12% of all AK20 participants). The number of observations is in each estimation is equal to 31,618. Panel B is based on the full estimation sample and assigns starting dates based on random draws from a uniform distribution of calendar months between July, 2017 and June, 2018. The number of observations in each estimation is equal to 31,797. Panel C is based on the full estimation sample and assigns starting dates based on the empirical distribution of actual starting dates of AK20 participants. The number of observations in each estimation is equal to 31,797. Panel D shows 2SLS estimates including different sets of covariates. Socioeconomic background controls for sex of the individual and whether the individual has a high school degree or higher. Labor market history includes information on whether the last employment spell was a blue-collar job, and an individuals' number of prior days in employment and unemployment. *Age*^{2} indicates the inclusion of a quadratic term for the running variable age. *Separate trends* uses separate trends of the running variable *age* on each side of the discontinuity. The number of observations in each estimation is equal to 31,797. * p<0.10, ** p<0.05, *** p<0.01.

Table A.5: Spillovers of regional AK20 intensity, dose treatment

	Outcome variable is *Duration in Unemployment*					
	(1) All	(2) Female	(3) Male	(4) Below 30	(5) 30 to 50	(6) Above 50
$share_r \times post_t$	0.467	0.583	0.597	0.141	0.313	0.575
	(0.695)	(0.559)	(1.000)	(0.490)	(0.852)	(0.696)
No. of observations	889,312	378,239	511,073	158,161	355,231	375,920
Mean of dep. variable	190.96	178.26	200.35	136.15	193.25	211.85

Notes: The dependent variable is the number of days in unemployment for (1) all, (2) females, (3) males, (4) below 30 years old, (5) 30 years or older and below 50 years old, and (6) above 50 years old. The table shows standardized coefficients. * p<0.10, ** p<0.05, *** p<0.01.

Table A.6: Descriptive statistics for the spouse estimation sample

	(1) Eligible	(2) Non eligible	(3) AK20 participants
Age	52.05	47.74	52.13
	(1.18)	(1.01)	(1.13)
Female	0.46	0.54	0.50
High school degree or higher	0.32	0.32	0.32
Prior days employed	3,422.09	3,014.78	3,758.19
	(2,018.91)	(1,927.62)	(1,869.55)
Prior days unemployed	2,118.60	2,126.10	1,966.01
	(1,378.94)	(1,349.58)	(1,212.61)
Model region	0.42	0.45	0.54
Partner employed at t=−12	0.53	0.52	0.57
Partner unemployed at t=−12	0.16	0.19	0.14
Partner retired at t=−12	0.07	0.04	0.05
No. of observations	3,792	2,701	362

Notes: Table A.6 presents summary statistics for the spouse estimation sample. This sample comprises all AK20 participants and long-term unemployed workers between 46 and 54 years of age for which we have information on their spouse (until 2007). Column 1 reports statistics for eligible individuals, Column 2 for non-eligible individuals, and Column 3 for AK20 participants (a subset of the eligible group). Each cell displays the arithmetic mean, with standard deviations shown in parentheses below for non-binary variables. Prior days employed and prior days unemployed are measured relative to July 2017, which marks the start of the AK20 spell (for participants) or the corresponding placebo spell (for non-participants). The labor market status of the partner (employed, unemployed, retired) is measured 12 months before ($t = -12$) the (placebo) start of the program.

Table A.7: Descriptive statistics for the children estimation sample

	(1) Eligible	(2) Non eligible	(3) AK20 participants
Parent age	52.05	47.78	52.11
	(1.18)	(1.02)	(1.13)
Parent female	0.54	0.63	0.61
Parent high school degree or higher	0.28	0.28	0.30
Parent prior days employed	3099.95	2712.01	3500.11
	(1951.47)	(1863.84)	(1845.86)
Parent prior days unemployed	2377.25	2314.02	2231.45
	(1440.90)	(1398.33)	(1327.94)
Parent model region	0.49	0.53	0.59
Parent nr. of children	1.97	2.00	1.86
	(0.99)	(1.05)	(1.07)
Child employed at t=−12	0.33	0.23	0.35
Child unemployed at t=−12	0.12	0.10	0.11
No. of observations parent	8,655	6,122	768
No. of observations children	17,083	12,231	1,426

Notes: Table A.7 presents summary statistics for the children estimation sample. This sample comprises all children (which we can identify until 2007) of AK20 participants and long-term unemployed workers between 46 and 54 years of age. Note that all rows indicated with *parent* refer to the descriptives about the parents (a subsample of our main sample). All rows indicated with *child* refer to the children of individuals from our main sample. Note that parents can have multiple children, thus the number of observations for children is larger than that of parents. Column 1 reports statistics for eligible individuals, Column 2 for non-eligible individuals, and Column 3 for AK20 participants (a subset of the eligible group). Each cell displays the arithmetic mean, with standard deviations shown in parentheses below for non-binary variables. Prior days employed and prior days unemployed are measured relative to July 2017, which marks the start of the AK20 spell (for participants) or the corresponding placebo spell (for non-participants). The labor market status of the child (employed, unemployed) is measured 12 months before ($t = -12$) the (placebo) start of the program.

Table A.8: Descriptive statistics for health estimation sample

	(1) Eligible	(2) Non eligible	(3) AK20 participants
Age	52.02	47.78	52.07
	(1.17)	(1.02)	(1.12)
Female	0.40	0.44	0.47
High school degree or higher	0.23	0.25	0.24
Prior days employed	3238.06	3035.60	3474.09
	(1938.60)	(1959.72)	(1797.02)
Prior days unemployed	2186.16	2032.95	2239.60
	(1360.31)	(1283.22)	(1271.31)
Model region	0.33	0.32	0.61
Health outcomes:			
Prior total health-care spending	229.12	236.18	221.54
	(234.52)	(259.80)	(231.81)
Prior outpatient health-care spending	66.05	62.39	65.69
	(33.60)	(30.61)	(33.26)
Prior inpatient health-care spending	132.39	140.27	124.29
	(204.37)	(211.45)	(193.19)
Prior spending on prescription drugs	30.68	33.53	31.56
	(88.20)	(140.36)	(127.09)
Prior spending on antidepressants	2.64	2.64	2.82
	(6.63)	(6.60)	(6.98)
No. of observations	1,817	1,303	310

Notes: Table A.8 presents summary statistics for the health outcome sample. Column 1 reports statistics for eligible individuals, Column 2 for non-eligible individuals, and Column 3 for AK20 participants (a subset of the eligible group). Each cell displays the arithmetic mean, with standard deviations shown in parentheses below for non-binary variables. Prior days employed and prior days unemployed are measured leading up to July 2017, which marks the start of the AK20 spell or the corresponding placebo spell. Prior health-care spending shows the average aggregate expenditure per month insured over the period 2005 until the (placebo) start of the AK20 spell (July 2017).

B Details of the back-of-the-envelope fiscal calculations

This appendix documents the arithmetic underlying the back-of-the-envelope fiscal calculations reported in the paper. The purpose of this exercise is to provide a transparent accounting of short- to medium-run fiscal flows associated with the AK20 program. It is not intended as a full welfare analysis.

Program costs

According to Walch and Dorofeenko (2020), total direct program costs amounted to 209 € million. With 3,815 program participants, average direct costs per participant are given by

$$\text{Cost per participant} = \frac{209{,}000{,}000}{3{,}815} = \text{Euro } 54{,}784.$$

Additional tax revenues

We assume that participants earn an annual income of 25,200 € following program participation. Based on this earnings level, we approximate additional tax payments of 1,125 € per year. Over the four-year observation window, cumulative tax revenues are therefore given by

$$\text{Additional taxes} = 1{,}125 \times 4 = \text{Euro } 4{,}500.$$

This calculation assumes constant annual earnings over the four-year period and abstracts from changes in the tax schedule.

Savings in unemployment benefit payments

Unemployment benefit savings are calculated using an average benefit replacement rate of 55%. AK20 participation reduced unemployment by 578 days in years 1–2 and by 164 days in years 3–4. Savings in unemployment benefit payments are therefore given by

$$\text{UI savings}_{1-2} = 578 \times \frac{25{,}200 \times 2}{730} \times 0.55 = \text{Euro } 21{,}948,$$

and

$$\text{UI savings}_{3-4} = 164 \times \frac{25{,}200 \times 2}{730} \times 0.55 = \text{Euro } 6{,}227.$$

Total unemployment benefit savings over the four-year period amount to

$$\text{Total UI savings} = 21{,}948 + 6{,}227 = \text{Euro } 28{,}176.$$

Savings in pension payments

Pension savings arise only in years 3–4, when AK20 participation reduces time spent in retirement by an average of 81 days. Applying a pension replacement rate of 80%, pension savings are calculated as

$$\text{Pension savings} = 81 \times \frac{25{,}200 \times 2}{730} \times 0.8 = \text{Euro } 4{,}473.$$

Total fiscal benefits

Summing the components above yields total fiscal benefits over the first four years of

$$\text{Total benefits} = 4{,}500 + 28{,}176 + 4{,}473 = \text{Euro } 37{,}149.$$

We do not include additional social security contributions — approximately 8,040 € in years 1–2 and 4,900 € in years 3–4 — as fiscal savings, since these payments generate future benefit entitlements.

Interpretation

Comparing total fiscal benefits of 37,149 € to average direct program costs of 54,784 € implies that approximately 68% of program costs are offset within the first four years after program start. This calculation excludes administrative costs, general equilibrium effects, and any fiscal benefits accruing beyond the four-year window.