South Carolina Reemployment Services and Eligibility Assessments (RESEA) Randomized Controlled Trial of Automated Job Referrals

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Abstract: In this study, we will estimate causal impacts of providing frequent, timely, and customized automated job vacancy referrals to unemployment insurance (UI) beneficiaries on job search, UI receipt and duration, and labor market outcomes. We will randomly assign South Carolina Reemployment Services and Eligibility Assessments (RESEA) participants to receive staff-assisted registration for an automated job referral service called Virtual Recruiter® (VR). While all of South Carolina's UI beneficiaries may register themselves for VR within the SCWorks Online System portal, participation in this service currently is quite low among RESEA participants. Thus, there is much scope for staff assistance in VR registration to increase participation in the service, to increase engagement with job vacancy postings, and, potentially, to speed reemployment and UI exit. We plan to enroll the RESEA population to the experimental treatment during a twelve-month period. We expect that the intervention will involve random assignment of about 17,000 UI beneficiaries referred to RESEA, providing power to detect effect sizes of magnitudes that we may reasonably expect.

1. Introduction

Job loss and long periods of joblessness, in particular, generate persistent earnings losses and negatively affect workers' physical and mental health (Jacobson, LaLonde, and Sullivan 1993; Couch and Placzek 2010; Krueger and Mueller 2012; Damaske 2021; Fallick et al. 2025). As such, interventions intended to speed reemployment have the potential to substantially improve displaced workers' long-term labor market outcomes and overall well-being.

In this study, we will estimate causal impacts of providing frequent, timely, and customized automated job vacancy referrals to unemployment insurance (UI) beneficiaries on job search, UI receipt and duration, and labor market outcomes. Such job referrals decrease the costs of job search and increase the productivity of search time and effort. Furthermore, timely referrals allow applicants to apply before the employer has received many competing applications.

We will conduct our study among participants in South Carolina's Reemployment Services and Eligibility Assessments (RESEA) program. RESEA provides UI eligibility assessments and reemployment services, including job-search support and staff-provided job referrals, to UI beneficiaries identified as most likely to exhaust their UI entitlement. In an implementation study report (Pepin et al. 2025), we find that there is considerable scope to speed reemployment by providing RESEA participants with additional relevant job referrals.

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We will randomly assign RESEA participants to receive staff-assisted registration for an automated job referral service called Virtual Recruiter® (VR) over a twelve-month period. Randomization will occur when a claimant is profiled for the first time as part of the existing RESEA profiling process.

While all of South Carolina's UI beneficiaries may register themselves for VR within the SCWorks Online System (SCWOS) portal, participation in this service currently is quite low among RESEA participants. Thus, during the initial RESEA appointment, RESEA analysts will register treatment group participants with VR (if they are not participating already). Treatment group participants will reserve the right to opt out of registration, and control group participants still will be able to register for VR on their own. Additionally, unless the RESEA participant opts out, the RESEA analyst will set treatment participants' VRs to run daily, explaining that this will allow them to view and apply for jobs as soon as they are posted. The RESEA analyst will recommend and assist treatment participants in opting into email or text message notifications that will alert them to their job referrals in case they do not login to the SCWOS portal every day and, unless the participant objects, will not change the default expiration date of 90 days from the date the VR is saved.

At each subsequent RESEA appointment, RESEA analysts will follow up with treatment participants who registered for VR. Specifically, they will ask each treatment participant whether they have been receiving job referrals from VR and, if so, whether those referrals have been relevant to the jobs in which they are most interested. If the treatment participant tells the RESEA analyst that their VR has not been sending relevant job referrals, the analyst will use their expertise and collaborate with the participant to edit the VR settings to better fit the job seeker's preferences. The RESEA analyst also will edit the VR to expire two months after the appointment so that it does not expire before the participant's next RESEA appointment.

Before implementing the full intervention, we plan to pilot it for about two months in the Columbia, SC area. During this pilot, we will closely monitor the following outcomes through qualitative and quantitative data collection and site visits:

- Whether randomization to treatment and control groups is being implemented properly,
- Whether there is balance in RESEA participant characteristics across treatment and control groups,
- Whether RESEA analysts are following the treatment protocol for treatment group participants,
- The proportions of RESEA participants in the treatment and control groups who register for VR,

- RESEA analyst experiences with implementing the intervention,
- Treatment participant experiences with the intervention, and
- Whether data systems are recording intervention outcomes accurately.

Data from the pilot will not be used in evaluating the effectiveness of the intervention.

2. Outcomes

We will evaluate the intervention using administrative data provided to us from the South Carolina Department of Employment and Workforce. We plan to study the following primary outcomes:

1) Full-time equivalent weeks of UI compensation

2) Total UI compensation received ($)

3) UI exhaustion rates

4) Employed, 2 quarters after benefit year begin (BYB) date

5) Earnings ($), 2 quarters after BYB date

6) Employed, 6 quarters after BYB date

7) Earnings ($), 6 quarters after BYB date

8) Cumulative earnings and UI compensation combined, 6 quarters after BYB date

9) Cumulative earnings, 6 quarters after BYB date

10) Probability that the first reemployment job is in the same 5-digit Standard Occupational Classification (SOC) code as the pre-claim job (conditional on employment by 6 quarters after BYB date)[2]

11) Probability that the first reemployment job is in the same 4-digit SOC code as the pre-claim job (conditional on employment by 6 quarters after BYB date)

12) Probability that the first reemployment job is in the same 3-digit SOC code as the pre-claim job (conditional on employment by 6 quarters after BYB date)

13) Probability that the first reemployment job is in the same 2-digit SOC code as the pre-claim job (conditional on employment by 6 quarters after BYB date)

[2] The outcomes 11-13 will be missing for many RESEA participants due to incomplete reporting. The South Carolina Department of Employment and Workforce sees about 80% compliance with reporting valid 6-digit SOC codes each quarter.

We also plan to study the number of job searches; i.e., clicks on links to job postings, conducted per week. We consider this a secondary outcome because we only can observe job searches for a select subset of jobs that are internally vetted by the South Carolina Department of Employment and Workforce.

Moreover, we plan to study the outcomes related to hourly wage and hours worked. We consider these secondary outcomes due to concerns about data quality. The South Carolina Department of Employment and Workforce has begun collecting hours worked in each quarter; however, this variable has not been validated and is not universally reported. If the hours data are of sufficient quality, we plan to study the following outcomes:

- Hourly wage rate, 2 quarters after BYB date (conditional on employment)
- Hourly wage rate share of pre-claim wage, 2 quarters after BYB date (conditional on employment)[3]
- Average weekly hours worked, 2 quarters after BYB date
- Hourly wage rate, 6 quarters after BYB date (conditional on employment)
- Hourly wage rate relative to pre-claim wage, 6 quarters after BYB date (conditional on employment)
- Average weekly hours worked, 6 quarters after BYB date
- Average weekly hours worked during quarters 2–6 quarters after BYB date
- Average hourly wage rate during quarters 2–6 after BYB date
- Average hourly wage rate share of pre-claim wage during quarters 2–6 after BYB date (conditional on employment during at least one of the quarters)

Additionally, we will use the method proposed by Athey et al. (2025) to study long-term employment and earnings outcomes that will not be observed for several years.

Lastly, we plan to test for balance in pre-treatment characteristics using the following variables: age, gender, race, ethnicity, education, veteran status, disability status, base period earnings, weekly benefit amount, potential UI duration, prior experience with the UI system as measured by the number of prior UI claims from January 2022 to December 2025, and RESEA profiling score.

3. Power Analysis

In this section, we conduct power analyses for the intervention. We plan to enroll the RESEA population to the experimental treatment during a twelve-month period to represent the full year. We expect that the intervention will involve random assignment of about 17,000 UI beneficiaries referred to RESEA, as 17,200 UI beneficiaries with benefit year begin dates from

[3] For multiple-job holders, we will use the pre-claim wage from the job with the highest base period earnings.

May 2023 to April 2024 were referred to the program. The RESEA population exhibited the following outcomes in recent years:

Table 1: UI and Labor Market Outcomes of the RESEA Population in Recent Years

Outcome	Time period	*N*	Mean	Standard deviation
Full-time equivalent weeks of UI compensation	BYB 5/23– 4/24	17,200	12.38	7.14
Total UI compensation received ($)	BYB 5/23– 4/24	17,200	3,735	2,302
Employed, 2 quarters after BYB date	BYB 2023Q1– 2023Q4	16,564	0.676	0.468
Earnings ($), 2 quarters after BYB date	BYB 2023Q1– 2023Q4	11,193	9,677	9,720
Employed, 6 quarters after BYB date	BYB 2022Q1– 2022Q4	13,149	0.707	0.455
Earnings ($), 6 quarters after BYB date	BYB 2022Q1– 2022Q4	9,301	10,539	8,970

NOTES: Outcomes of the RESEA population with the given benefit year begin (BYB) dates. *N*'s for earnings outcomes are conditional on having strictly positive earnings, though we will not condition on having strictly positive earnings in our analyses.

SOURCE: South Carolina Department of Employment and Workforce administrative program data.

We estimate that, given an expected 17,000 UI beneficiaries selected for RESEA equally divided between treatment and control groups, a power level of 0.8, and the means and standard deviations in outcomes listed in Table 1, we will be able to detect the following effect sizes:

Table 2: Detectable Differences in Outcomes

Outcome	Two-sided hypothesis test, 5% significance level	Two-sided hypothesis test, 10% significance level	One-sided hypothesis test, 5% significance level	One-sided hypothesis test, 10% significance level
Full-time equivalent weeks of UI compensation	0.31	0.27	0.27	0.23
Total UI compensation received ($)	99	88	88	75
Employed, 2 quarters after BYB date	0.020	0.018	0.018	0.015
Earnings ($), 2 quarters after BYB date	418	371		
Employed, 6 quarters after BYB date	0.020	0.017	0.017	0.015
Earnings ($), 6 quarters after BYB date	386	342		

NOTES: Estimated detectable effect sizes for UI and labor market outcomes among the RESEA population. Estimates are based on a population of 17,000 and a power level of 0.8.

Hypothetical impact estimates listed in Table 2 suggest that we will be able to detect impact magnitudes large enough to be of policy interest. Employment interventions tend to yield effects on average UI duration of about –0.5 weeks and decreases in average UI compensation during the benefit year of about half the average UI weekly benefit amount.[4]

[4] See Almandsmith, Ortiz Adams, and Bos (2006); Black et al. (2003); Corson et al. (1989); Corson and Haimson (1996); Corson, Long, and Nicholson (1985); Johnson and Klepinger (1994); Klepinger et al. (1997); Klerman et al.

4. Empirical Specification

We will estimate intent-to-treat (ITT) and treatment-on-the-treated (TOT) effects of being assigned to the treatment condition, relative to the control condition. In other words, we will estimate impacts of UI beneficiaries being assigned to receive staff-assisted VR registration and follow-up and effects among those who successfully receive this service. We first will estimate the following ordinary least squares equation:

(1) $y_{ist} = \beta_0 + \beta_1 TREATMENT_i + \beta_2 X_i + \lambda_{st} + \epsilon_{ist}$,

where y_{it} is the outcome of interest for individual *i* who is served by local American Job Center *s* and was referred to RESEA during calendar quarter *t*. $TREATMENT_i$ equals 0 for UI beneficiaries assigned to the control group and equals 1 for beneficiaries assigned to the treatment group. X_i is a set of individual characteristics, such as age, sex, and race included to improve power. λ_{st} is an American Job Center-calendar quarter fixed effect that accounts for differences in service provision and employment opportunities across local areas over time. ϵ_{it} is the heteroskedasticity-robust error term.[5] β_1 is the coefficient of interest and measures the average impact of being assigned to receive staff-assisted VR registration and follow-up.

Because beneficiaries assigned to the treatment group who refuse the treatment, return to work quickly, or fail to meet RESEA requirements may not receive staff-assisted VR registration, we also will estimate TOT impacts among those who end up receiving this service. We model this as follows:

(1) $y_{ist} = \pi_0 + \pi_1 VR_i + \pi_2 X_i + \phi_s + \phi_t + \nu_{ist}$,

where VR_i equals 0 for UI beneficiaries who do not receive staff-assisted VR registration and equals 1 for beneficiaries who receive it. All other variables are similar to those in equation (1). We estimate equation (2) using two-stage least squares with the following first-stage equation:

(2) $VR_{ist} = \delta_0 + \delta_1 TREATMENT_i + \delta_2 X_i + \rho_s + \rho_t + \mu_{ist}$.

We interpret the $\widehat{\pi_1}$ on equation (2) as a local average treatment effect of staff-assisted VR registration and follow-up. In other words, our estimate of π_1 identifies the causal impact of VR registration and follow-up among the subset of UI beneficiaries who receive the treatment.

4.1. Prespecified Heterogeneity

(2019); Meyer (1995) Michaelides et al. (2012); Michaelides and Mueser (2018); O'Leary et al. (2022); and Pepin et al. (2023).

[5] We also will estimate models that do not control for individual characteristics and do not include American Job Center and calendar quarter fixed effects. As these covariates will not be correlated with treatment probability, they are not needed for β_1 to yield an unbiased impact estimate of the treatment. Nevertheless, including such covariates can improve power by accounting for chance difference in variables between the treatment and control groups.

Additionally, we will examine heterogeneity in treatment effects across different subgroups. We will explore whether treatment effects differ by UI claimant characteristics including age, gender, race, ethnicity, education, veteran status, disability status, base period earnings, weekly benefit amount, potential UI duration,[6] prior experience with the UI system as measured by the number of prior UI claims from January 2022 to December 2025, and RESEA profiling score. To account for multiple hypothesis testing, we will report false discovery rate corrected *p*-values.

We plan to explore heterogeneity by prior job search intensity as measured by the number of clicks on links to internally-vetted job postings per week during the waiting week and first payable week and, for those who attend the first RESEA appointment, the number of clicks before the first RESEA appointment scheduled date. We will explore heterogeneity by tightness of the local labor market using the average monthly county unemployment rate from the U.S. Bureau of Labor Statistics during the month of the claim and the two subsequent months. Additionally, we will examine heterogeneity by the job seeker's pre-claim two-digit industry or occupation group using the number of vacancy postings in the given industry or occupation group-quarter from Lightcast relative to the number of UI claimants in South Carolina in that same industry or occupation-quarter from the U.S. Department of Labor's ETA 203 report.

Lastly, we plan to use the causal random forest method (Wager and Athey 2018) to flexibly identify heterogeneity by potentially complicated, high-dimensional, non-linear functions of observables. This method will allow us to identify whether there is a group for which the intervention is particularly effective. If the causal forest does not detect heterogeneity, this suggests that either treatment effect heterogeneity is driven by unobservables or the treatment effect is homogeneous. To interpret the output of the causal forest, i.e., predicted treatment effects for each individual in our analysis sample, we plan to split the sample into quantiles of the predicted treatment effect and report descriptive statistics for each quantile. Additionally, we plan to use the output of the causal forest model to explore mechanisms by examining how predicted treatment effects for our prespecified outcomes correlate with one another. For example, if the causal forest were to indicate that treatment effects on weeks of UI compensation and on earnings six quarters after the BYB date are inversely correlated, this would suggest that individuals whose reemployment was accelerated by the intervention tended to accept lower-paying jobs.

[6] Around 88 percent of RESEA participants are eligible for 20 weeks of UI. The remaining 12 percent are eligible for between 13 and 19 weeks of UI.

5. Works Cited

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