Assessing the Performance of Targeted Workforce Interventions: A Propensity Score Matched Interrupted Time Series Analysis of Alabama's RESEA Program.

Alabama Department of Workforce

Labor Market Information Division

Prepared for the

U.S. Department of Labor

Clearinghouse for Labor Evaluation and Research

July 2026

Author

Hallory Tucker

Workforce Alabama

Table of Contents

I. Introduction 3
II. Literature Review 3
A. Empirical Evidence for Mandatory Interventions 4
B. The Impact of Early Interventions 4
C. Targeting Optimization and Model Recalibration 4
III. The Alabama RESEA Program and 2023 Model Update 5
A. The 2023 Model Recalibration 6
IV. Internal Validity 6
V. Methodology 8
A. Data Collection and Integration 9
B. Temporal Alignment and Policy Intervention 10
C. Accounting for the January 2023 Policy Intervention 10
D. Covariate Balance and Matching 10
E. The Propensity Score Matched Interrupted Time Series Framework 11
VI. Results 12
A. Reemployment Velocity 12
B. Wage Recovery 13
C. Fiscal Implications 13
VII. Limitations 13
VIII. Discussion 14
A. Future Directions 15

Abstract

The Alabama Department of Workforce (ADOW) implemented a major recalibration of its Reemployment Services and Eligibility Assessment (RESEA) profiling model in January 2023 to improve the efficiency of unemployment insurance (UI) program administration during a period of historically low unemployment. The revised model expanded claimant eligibility by removing prior education, occupation, and industry exclusions while accelerating intervention timing to engage claimants earlier in the unemployment spell. This study evaluates the impact of these changes using a Propensity Score Matched Interrupted Time Series (PSM-ITS) design based on administrative data from 355,784 longitudinal observations representing 16,305 RESEA participants and an equal-sized matched comparison group across 11 intervention cohorts.

Nearest-neighbor propensity score matching was used to balance demographic characteristics between treatment and control groups, followed by fixed-effects regression with clustered standard errors to estimate program impacts on unemployment duration and post-program earnings. To ensure comparability across cohorts spanning multiple years, all quarterly earnings were adjusted to constant 2023 dollars using the Consumer Price Index for All Urban Consumers (CPI-U), reducing the influence of inflation and broader macroeconomic price changes on estimated wage effects. Results indicate that the 2023 profiling model significantly accelerated reemployment, reducing unemployment duration by approximately one-half week post-intervention quarter ($\beta = -0.821$, $p < 0.001$). Participants also experienced significantly stronger wage recovery, earning an additional average of $537 per quarter than matched nonparticipants ($p < 0.001$). These improvements translated into an estimated $1.96 million in UI Trust Fund savings across post-policy cohorts through reduced benefit duration.

These findings demonstrate that the expanding and accelerating RESEA targeting can simultaneously improve claimant employment outcomes and strengthen UI Trust Fund sustainability. The study provides rigorous evidence supporting data-driven profiling strategies and offers a replicable evaluation framework for workforce agencies seeking to optimize reemployment services while maintaining fiscal responsibility.

I. Introduction

The integrity of the Unemployment Insurance (UI) Trust Fund is a primary fiscal priority for the state of Alabama. While the state has maintained historically low unemployment rates through FY2023 and into FY2024, this trend presents a unique structural challenge: the remaining pool of claimants often face significant barriers to reemployment, increasing the risk of long-term dependency and benefit exhaustion. To address this, the Alabama Department of Workforce (ADOW) utilizes the Reemployment Services and Eligibility Assessment (RESEA) Program to provide evidence-based interventions for high-risk claimants.

Central to this effort is the RESEA profiling model, maintained by the Labor Market Information (LMI) division. The 2023 update to the Profiling Model reflects a strategic shift towards fiscal sustainability. By removing previous exclusions for high-education and high-occupation claimants, ADOW targets "high-value" claims that represent a significant potential draw on the UI Trust Fund. Although these individuals statistically return to work faster, the mandatory intervention ensures that this transition is not delayed, minimizing total benefit payouts while maximizing the return on investment for the RESEA grant.

This study employs a Propensity Score Matched Interrupted Time Series (PSM-ITS) framework to conduct a formal impact evaluation of the RESEA program following the 2023 model update. Using data from 11 distinct cohorts and over 350,000 observations, we test the hypothesis that the expanded profiling logic successfully accelerated reemployment speed and improved the quality of labor market outcomes. Specifically, the study measures the change in the number of weeks claimants remain on the UI system and their subsequent quarterly wage recovery, providing a transparent, evidence-based assessment of the program's efficacy that aligns with federal standards.

II. Literature Review

Current evaluations of reemployment programs emphasize the use of rigorous, evidence-based frameworks to establish a clear link between intervention and outcome. This study builds upon three primary pillars of existing research: the efficacy of mandatory interventions, the "threat effect" of program participation, and the optimization of targeting models.

A. Empirical Evidence for Mandatory Interventions

The foundational evidence for RESEA-style programs is established by the seminal Nevada study (Michaelides et al., 2012). This quasi-experimental evaluation demonstrated that claimants receiving mandatory reemployment services and eligibility assessments experienced significantly shorter unemployment durations and higher long-term earnings than the control group. Michaelides et al. (2012) found that the combination of job search assistance and strict eligibility monitoring reduced UI benefit draws by approximately 1.8 weeks. This research provides the theoretical basis for Alabama's current model, suggesting that the integration of career counseling with compliance reviews creates a synergistic effect that accelerates reemployment.

B. The Impact of Early Interventions

A secondary area of literature explores the "threat effect," or the behavioral nudge provided by the requirement of the recently unemployed to attend a mandatory meeting. Black et al. (2003) discovered that a significant portion of the reduction in UI duration occurs immediately after a claimant is notified of their selection for services, often before the first meeting takes place. This finding supports the 2023 update to Alabama's Profiling Model, which accelerated the intervention timeline to maximize the "threat effect". Previously, the profiling logic utilized a "two weeks paid" threshold, delaying intervention until benefit payments were fully processed. The updated model shifted this trigger to "two weeks certified", initiating engagement as soon as a claimant verifies their active search for work and ongoing eligibility. By moving the intervention forward, the state leverages this behavioral nudge at the onset of the claim, maximizing the potential for early return-to-work and establishing a proactive reemployment trajectory.

C. Targeting Optimization and Model Recalibration

The efficacy of these programs is heavily dependent on the accuracy of the profiling logic used to select participants. Research by Poe-Yamagata et al. (2011) emphasizes that as labor market conditions tighten, profiling models must be recalibrated to include a broader range of claimants, including those with higher educational attainment or specialized skills who may have previously been excluded. This study situates the January 2023 recalibration of the Alabama Profiling Model within this context. As noted in the FY 2024 State Plan, the removal of previous occupation and education filters reflects a modern transition toward capturing claims that represent a significant potential impact on the UI trust fund.

By utilizing a Propensity Score Matched Interrupted Time Series (PSM-ITS) design, this study bridges the gap between historical targeting research and current administrative data. This approach allows for a precise estimation of program impact that accounts for the non-random nature of claimant selection.

III. The Alabama RESEA Program and 2023 Model Update

The RESEA Program in Alabama is managed through a collaborative team consisting of senior staff from the Alabama Department of Workforce Employment Services (ES), Unemployment Insurance (UI), and Labor Market Information (LMI) divisions. The program is statewide and operates out of America's Job Centers (AJCs), where Wagner-Peyser merit staff conduct mandatory interventions for selected claimants.

The intervention is designed as a comprehensive entry point for UI recipients into the broader workforce system. It consists of a one-on-one seated interview that includes UI eligibility review, an individual assessment to identify barriers, and the development of a signed Individual Employment Plan (IEP). As of the FY 2024 period, ADOW has streamlined these activities to be completed in approximately 3.5 hours, focusing on intensifying virtual and remote service delivery.

A critical component of this study's internal validity is the rigid, deterministic nature of participant selection. Claimants are entered into the profiling pool at the time they are determined eligible for benefit payments. Selection is conducted automatically every Friday morning by an external state data information vendor based on LMI's proprietary profiling model. Because this logic is governed by a complex algorithm, the specific intervention date remains unpredictable to the claimant.

Once selected, claimant participation in the intervention becomes a mandatory condition of UI eligibility. Claimants are mailed a notification letter by the end of business on the day of selection, providing an appointment date for the following week. Failure to report or participate in any aspect of the scheduled RESEA meeting results in an automated referral to the UI agency for adjudication, often leading to the denial of benefits.

A. The 2023 Model Recalibration

In January 2023, the ADOW RESEA Team implemented a strategic recalibration of the profiling logic to adapt to Alabama's historically low unemployment rates and to ensure fiscal sustainability. This update represents the primary "intervention" point for this Interrupted Time Series analysis. The recalibration introduced three fundamental shifts in program targeting:

- Expanded Participant Pool: The model removed previous filters related to Education Level, Occupation (SOC Codes), and Industry of Employment, specifically to target "high value" claims that represent a significant potential draw on the UI Trust Fund.
- Increased Selection Frequency: The updated logic allowed claims to be added to the selection pool multiple times based on the number of weeks filed, ensuring consistent engagement with claimants who remain unemployed.
- Removal of Recency Restrictions: The update removed the filter that previously rolled off claims filed more than five weeks prior, effectively broadening the longitudinal window for intervention.

These changes resulted in a significant increase in the number of scheduled RESEA participants, rising by over 50 percent compared to the previous year, despite the statewide unemployment rate remaining largely unchanged. This study evaluates the impact of this expanded, earlier intervention logic on the speed of reemployment and the quality of subsequent labor market outcomes.

IV. Internal Validity

To ensure the reliability of the estimated causal effects, each claimant was tracked over a longitudinal window of 21 quarters, with the analysis focusing on the five quarters immediately preceding and following the intervention quarter. To account for temporal variations in purchasing power, all quarterly earnings were deflated to 2023 constant dollars using the Consumer Price Index for all Urban Consumers (CPI-U). This five-and-five observational framework satisfies the requirements for high-level evidence by enduring that pre-existing trend such as the "Ashenfelter's Dip", the temporary earnings decline often observed prior to program entry, are fully stabilized (Ashenfelter, 1978). As illustrated in Figure 1, the treatment and control groups exhibit nearly identical pre-intervention trajectories across all cohorts, validating the parallel trends assumption. Furthermore, the presence of Ashenfelter's dip immediately prior to quarter 6 confirms that the model captures the transient earnings decline typical of claimants entering the UI system, thereby isolating the post-intervention treatment effect from pre-existing demographic and economic shocks.

To address potential anticipation effects, it is noted that while the RESEA program is a standard component of the UI system, the specific timing of a claimant's selection and subsequent meeting dates are not disclosed to the individual until a formal notification is issued. Because the selection logic is governed by a complex profiling model maintained by the LMI Division, the precise intervention variable remains unpredictable to the claimant during the early stages of their claims.

A fundamental strength of this research design is the deterministic nature of the intervention timing. The intervention period was not determined by the individual claimant, the local career center staff, or any subjective assessment of a claimant's progress. Instead, the intervention schedule was established by a rigid administrative protocol maintained by the LMI Division and executed through an external UI State Data Information Vendor. Selection for RESEA services is triggered automatically once a claimant reaches a predetermined milestone, the second week of certified unemployment. Because this timing is programmed into the system, it is immune to manipulation by the entities being studied. There is no mechanism for a claimant to volunteer for an earlier intervention, nor can a caseworker delay the intervention based on the claimant's perceived readiness. This ensures that the implementation of the treatment is predetermined, providing additional assistance that the estimated effects on reemployment and wages are the result of the program itself rather than endogenous selection or administrative bias.

Rather than relying on a concurrent control group, which can introduce selection bias or contamination through spillover effects, this study utilizes a controlled ITS framework that incorporates a distinct control group of claimants alongside the intervention group. While the ITS component leverages the temporal stability of the claimant population to establish pre-intervention trends, the inclusion of a concurrent control group allows for the direct comparison of post-intervention outcomes between treated and untreated cohorts. This hybrid design effectively neutralizes time varying confounding factors such as seasonal labor market shifts or regional economic fluctuations that would otherwise affect groups simultaneously. By anchoring the analysis on the deterministic, system-wide implementation of RESEA, the model isolates the treatment effect as the differential deviation between the intervention group's trajectory and the control group's counterfactual baseline, thereby providing a more rigorous validation of the program's impact than either design could offer in isolation.

Finally, this evaluation maintains high internal validity by rigorously managing sample composition across the 11 study cohorts. Because UI eligibility requirements remained constant throughout the evaluation period (2021 Q4 to 2024 Q2), the claimant population remained demographically and economically consistent, mitigating risks of selection bias at entry. Furthermore, by treating the exit of claimants from the UI system as a primary outcome of interest, rather than a migration pattern, this study aligns the data directly with the RESEA program's goal of facilitating rapid reemployment. Given the scale of the state-wide dataset (n = 355, 784), the model possesses the statistical stability necessary to ensure that observed behavioral transitions represent genuine program-driven impacts over random fluctuations in sample characteristics.

V. Methodology

This study utilizes a Propensity Score Matched Interrupted Time Series (PSM-ITS) design to measure the effectiveness of RESEA interventions. This design combined two rigorous evaluation techniques to isolate the program's causal impact. First, Propensity Score Matching (PSM) addressed selection bias by creating a synthetic control group that mirrored the demographic and baseline characteristics of RESEA participants. This ensured that any observed differences in outcomes were due to the intervention rather than pre-existing demographic disparities. Second, the Interrupted Time Series (ITS) framework tracked claimant outcomes over a 21-quarter longitudinal window. By comparing the intervention group's trajectory against both their own pre-program trends and the performance of the matched control group, this model effectively neutralized confounding factors such as seasonal labor market shifts or regional economic fluctuations. To address potential selection bias inherent in administrative program participation, we employed Nearest Neighbor Propensity Score Matching to construct a synthetic control group. The effectiveness of this matching process was verified by assessing the Standard Mean Difference (SMD) for all demographic covariates (Age, Education, Gender, and Veteran Status). As confirmed by our balance assessment, all covariates achieved an Absolute Mean

Difference of less than 0.1 post-matching, verifying that the control group is an appropriate counterfactual for the treated population. The analysis utilizes administrative data from the Alabama Department of Workforce. Detailed definitions for all variables, included adjustments for inflation and temporal mapping, are provided in the Data Dictionary (See Appendix C).

A. Data Collection and Integration

The primary dataset consists of 355,784 observations extracted from the LMI server. This data consists of 16,305 RESEA Participants and their matched control counterparts over a 21-quarter window (five quarters pre-intervention, the intervention quarter, and five-quarters post-intervention). Additionally, we split RESEA Participants and their control counterparts into 11 different cohorts based on intervention quarter. Data synthesis was executed via a multi-stage SQL integration across three primary state databases (See Figure 2 for a detailed Workflow):

- **RESEA Database (Cohort Identification):** The RESEA population was established by identifying all RESEA participants between 2021 Q4 and 2024 Q2. This established the "intervention date" (Time 0) for each unique claimant ID.
- **PROMIS Database (Status Verification):** To determine labor market status, the cohort was joined with PROMIS administrative records. We utilized claim dates to verify periods of unemployment and to calculate the duration of benefit draws relative to the RESEA intervention. To establish a counterfactual, we identified a pool of non-RESEA claimants from the same 2021 Q4-2024 Q2 window, from which a control group was selected via the propensity score matching process described below.
- **UIWage Database (Earnings History):** Finally, a longitudinal join was performed with the UIWage database covering a five-year window (2020 Q3 to 2025 Q3). Wages were aggregated by ID to create a comprehensive pre- and post- intervention financial profile, capturing the economic trajectory of claimants before entering the program and following their return to work.

By utilizing this multi-stage join process, we created a comprehensive longitudinal record for each claimant, ensuring that the final analytical model compares identical economic cohorts across staggered temporal windows.

B. Temporal Alignment and Policy Intervention

The study applies a “Small Multiples” approach by segmenting the data into 11 distinct temporal cohorts. Each cohort is anchored to its own unique intervention date ($Time_0$), allowing us to align pre- and post-intervention periods across different calendar windows. To better visualize the structural shift in our participant groups, Table 1 outlines the intervention quarters and the corresponding windows for each of the 11 cohorts. As shown, the January 2023 policy intervention marks the transition point for Cohort 6 and beyond.

C. Accounting for the January 2023 Policy Intervention

While every cohort experiences the RESEA intervention at their respective $Time_0$, Cohort 6 (2023 Q1) marks a structural shift. This cohort is the first to begin following the January 2023 Profiling Model recalibration. By treating the entry quarter as the anchor ($Time_0$), our design effectively isolates the program’s consistent baseline effects from the trajectory shift introduced by the updated policy criteria. This allows the model to measure whether the intervention’s efficacy intensified following the recalibration, providing a natural experiment within the broader 11-cohort framework.

D. Covariate Balance and Matching

To ensure the internal validity of our estimates, we employed Propensity Score Matching (PSM) to construct a counterfactual control group comparable to the RESEA participating cohort. We utilized a 1:1 nearest-neighbor matching algorithm without replacement, based on the predicted probability of participation derived from a logistic regression model incorporating age, education, gender, and veteran status.

The efficacy of this matching process is validated by the reduction in Standardized Mean Difference (SMD) across all covariates. Before matching, the sample exhibited significant imbalances, particularly regarding Age (SMD: 0.31) and specific categorical variables. Post-matching these imbalances were substantially attenuated (See Figure 3), as the SMD for key covariates now falls well within the conventional threshold of <0.10, indicating high covariate balance between the treated and matched control samples.

Furthermore, the matching procedure successfully reduced the sample size to 32,610 unique participants, creating a balanced panel of 16,305 treated and 16,305 control individuals. This rigorous balancing procedure minimizes selection bias, supporting the assumption that the observed differences in reemployment outcomes are attributable to the RESEA intervention rather than preexisting demographic disparities.

Following the identification of the matched sample, we extracted the specific participant IDs using a matching function. We then applied these identifiers to our longitudinal master dataset to construct the final object. This filtering process ensures that our subsequent longitudinal analysis is restricted to the 32,610 individuals that satisfy the criteria for balanced covariate representation across all 11 observed quarters.

To facilitate a time-series approach, we mapped the quarterly observations to a continuous numerical scale (t = 1 to t = 11), where t = 6 corresponds to the quarter of the RESEA intervention (target). While the base model assumes a universal intervention at time t = 6, the administrative policy changes specifically targeting the new profiling model was implemented for cohorts exceeding 6. Consequently, the interaction terms in our fixed-effect regression model are restricted to the subset of the population where Cohort > 6 and Time > 6. This refinement ensures that our estimates isolate the impact of the profiling model update from the general REA service delivery effects.

E. The Propensity Score Matched Interrupted Time Series Framework

This design isolates the program's impact from seasonal fluctuations or localized economic shocks. We utilized a clustered fixed-effects regression model to estimate the impact of the intervention (see Appendix B):

$$\boldsymbol{Y_{it} = \beta_0 + \beta_1(Resea_i) + \beta_2(Post_t) + \beta_3(Time_t) + \beta_4(Resea_i \times Post_t) + \beta_5(Resea_i \times Time_t) + \beta_6(Post_t \times Time_t) + \beta_7(Resea_i \times Post_t \times Time_t) + \alpha_i + \gamma_c + \epsilon_{it}}$$

Where:

- $\boldsymbol{Y_{it}}$: The outcome Variable (e.g. number of weeks unemployed or total quarterly wages)
- $\boldsymbol{\alpha_i}$: Represents the individual fixed effects, which absorb all the time-invariant unobserved heterogeneity.

- $\boldsymbol{\gamma_c}$: Represents the cohort fixed effects, controlling for temporal variations across implementation windows.
- $\boldsymbol{\beta_7}$: is the primary coefficient of interest (The triple interaction), representing the divergence in trajectory between RESEA participants and the control group post-intervention.
- $\boldsymbol{\varepsilon_{it}}$: Standard errors are clustered at the individual level (ID) to account for intra-claimant correlation over time.

The architecture of this study provides maximum statistical power through an 11-fold replication strategy. Rather than relying on a single temporal point, the staggered entry of claimants allows for rigorous internal control. By demonstrating consistent outcomes across 11 distinct cohorts, the model effectively isolates the program's impact from broader labor market trends. As outlined in Appendix Am the analysis utilized a *fixest* framework (*feols*), which handles high-dimensional fixed effects and clustered standard errors, ensuring that the reported t-statistics and p-values remain robust against the variance inherent in administrative wage data.

VI. Results

To isolate the program effect, we employed a triple-difference (DDD) specification. By interacting with the treatment status (is_resea) with the post intervention indicator (is_post_policy) and the time trend (time_numeric), we control baseline differences in unemployment duration, systematic time-varying shifts, and group specific trends (See Appendix C). The full results of this model, encompassing both total wage recovery and weeks of unemployment, are summarized in Table 2.

A. Reemployment Velocity

The triple interaction coefficient of -0.82 ($p < 0.001$) provided a robust estimate of the program's effect on the slope of the unemployment duration trajectory, effectively netting out confounding secular trends. This coefficient indicates that after the intervention, the unemployment duration for RESEA participants does not merely shift; it indicates that RESEA participants re-enter the workforce more rapidly than the control group. For every quarter post-intervention, the RESEA cohort achieves a relative reduction of approximately 0.5 weeks in unemployment duration, a finding that is highly precise given the scale of the dataset (see Figure 4 for visualization).

B. Wage Recovery

The analysis of quarterly wage recovery demonstrates that the RESEA program's mandatory intervention also positively impacts the claimant's earnings trajectory. The triple-interaction coefficient for the wage model is 537 ($p < 0.001$). This positive coefficient demonstrates that RESEA participants are achieving higher quarterly wage recovery compared to their counterparts in the control group (See Figure 5). These findings suggest that the individualized reemployment planning (IEP) and eligibility assessments act as a catalyst for higher quality job matching.

C. Fiscal Implications

The recalibration of the RESEA profiling model has yielded significant cost-avoidance for the UI Trust Fund, driven by accelerated claimant reemployment. This impact is fiscally significant; using the product of average weekly benefits, the cohort-specific savings coefficient, and the total number of RESEA participants, we estimate the quarterly savings of each cohort. Aggregating these impacts specifically for the post-policy cohorts specifically for the post-policy cohorts (2023 Q1 through 2024 Q2), the cumulative reduction in benefit drawdown results in an estimated total savings of $1,958,702 for the UI Trust Fund. This figure represents a conservative estimate of the direct cost-avoidance achieved through accelerated reemployment following the 2023 model recalibration, further bolstered by the long-term fiscal multiplier effect of increased wage contributions. Table 3 provides a detailed breakdown of these quarterly savings estimates across the study period.

VII. Limitations

While the findings presented in this study provide evidence of the program's efficacy, the scope of this study is subject to certain limitations that merit consideration. First, regarding methodological constraints, although propensity score matching effectively balances observed demographic and baseline characteristics, the potential for unobserved heterogeneity remains a factor. Some examples of unobserved heterogeneity would be variations in individual job-search intensity or unrecorded outside employment opportunities. Furthermore, as this analysis focuses on a specific regional Unemployment Insurance (UI) system, these results should be interpreted as localized evidence of program impact, providing a foundational baseline for future multi-state comparative studies.

Second, from a fiscal and behavioral perspective, these estimates reflect a gross impact rather than a net welfare analysis. Consequently, they do not account for potential displacement effects or the administrative costs of program delivery. Future research could further refine these findings by conducting a formal cost-benefit analysis that offsets operational expenditure against documented savings. Finally, the “threat effect” identified by Black et al. (2003) warrants continued study. It remains possible that a portion of our observed success is driven by the behavioral nudge of mandatory participation itself, rather than the content of the services provided. Nevertheless, this study confirms that the systematic application of data-driven targeting is a highly effective mechanism for maintaining the integrity of the UI system in a dynamic economy.

VIII. Discussion

The outcomes observed in the post-policy intervention cohorts are directly attributable to the strategic recalibration of the profiling model. By removing previous exclusions based on education, occupation, and industry, ADOW effectively captured a broader demographic of claimants, specifically those representing claims that carry a greater potential impact on the UI Trust Fund. By employing a Propensity Score Matched Interrupted Time Series (PSM-ITS) design, we have isolated the causal impact of the RESEA program, demonstrating that the 2023 profiling recalibration successfully accelerated claimant return to work trajectories while simultaneously enhancing the quality of job matches.

Our analysis of reemployment velocity revealed a significant divergence in outcomes post-intervention. The triple interaction coefficient of -0.821 ($p < 0.001$) provided robust evidence that the program’s impact is not a temporary “shock”, but a sustained deceleration in unemployment duration. This result aligns with seminal work of Michaelides et el. (2012), reinforcing the theory that the combination of structured job search assistance and compliance monitoring creates a synergistic effect that benefits both the claimant and the UI trust fund. Furthermore, the magnitude of the wage recovery effect, an increase of $537 per quarter, challenges the “work-first” critique that mandatory programs merely force claimants into low-quality, temporary roles. Instead, our findings suggest that the individualized Employment Planning (IEP) process acts as a catalyst for effective labor market reintegration.

From a fiscal perspective, the estimated $1.98 million in cost-avoidance underscores the program's role as a cornerstone of state fiscal sustainability. By capturing "high value" claims that represent significant potential drains on the trust fund, ADOW has transformed RESEA from a standard compliance requirement into a sophisticated tool for labor market optimization.

A. *Future Directions*

While this study confirms the program's immediate efficacy, future research will aim to expand upon these findings in three critical areas. First, we plan to incorporate a longer-term longitudinal analysis to track whether these wage gains persist beyond the current 21 quarter window. Second, we intend to integrate additional data sources to better account for unobserved heterogeneity, specifically by incorporating industry-specific job-search indicators. Finally, a formal cost-benefit analysis will be conducted to compare the program's operational expenditure against the documented $1.98 million in UI Trust Fund savings. These steps will ensure that the RESEA profiling model continues to evolve alongside Alabama's dynamic labor market.

References

Ashenfelter, O. (1978). Estimating the effect of training programs on earnings. *The Review of Economics and Statistics*, 60(1), 47–57.

Black, D. A., Smith, J. A., Berger, M. C., & Noel, B. J. (2003). Is the threat of training more effective than training itself? Experimental evidence from the UI system. *The American Economic Review*, 93(4), 1013–1027.

Michaelides, C., Poe-Yamagata, E., Benus, J., & Tirumalasetti, D. (2012). *Impact Evaluation of the RESEA Program*. USDOL Office of Policy Development and Research.

Poe-Yamagata, E., et al. (2011). *Profiling and Referral to Reemployment Services: A Review of State Practices*. USDOL Employment and Training Administration.

Appendix A

Figures

Figure 1 Median Quarterly Wages by Cohort: Evidence of Parallel Trends and the Ashenfelter's Dip.

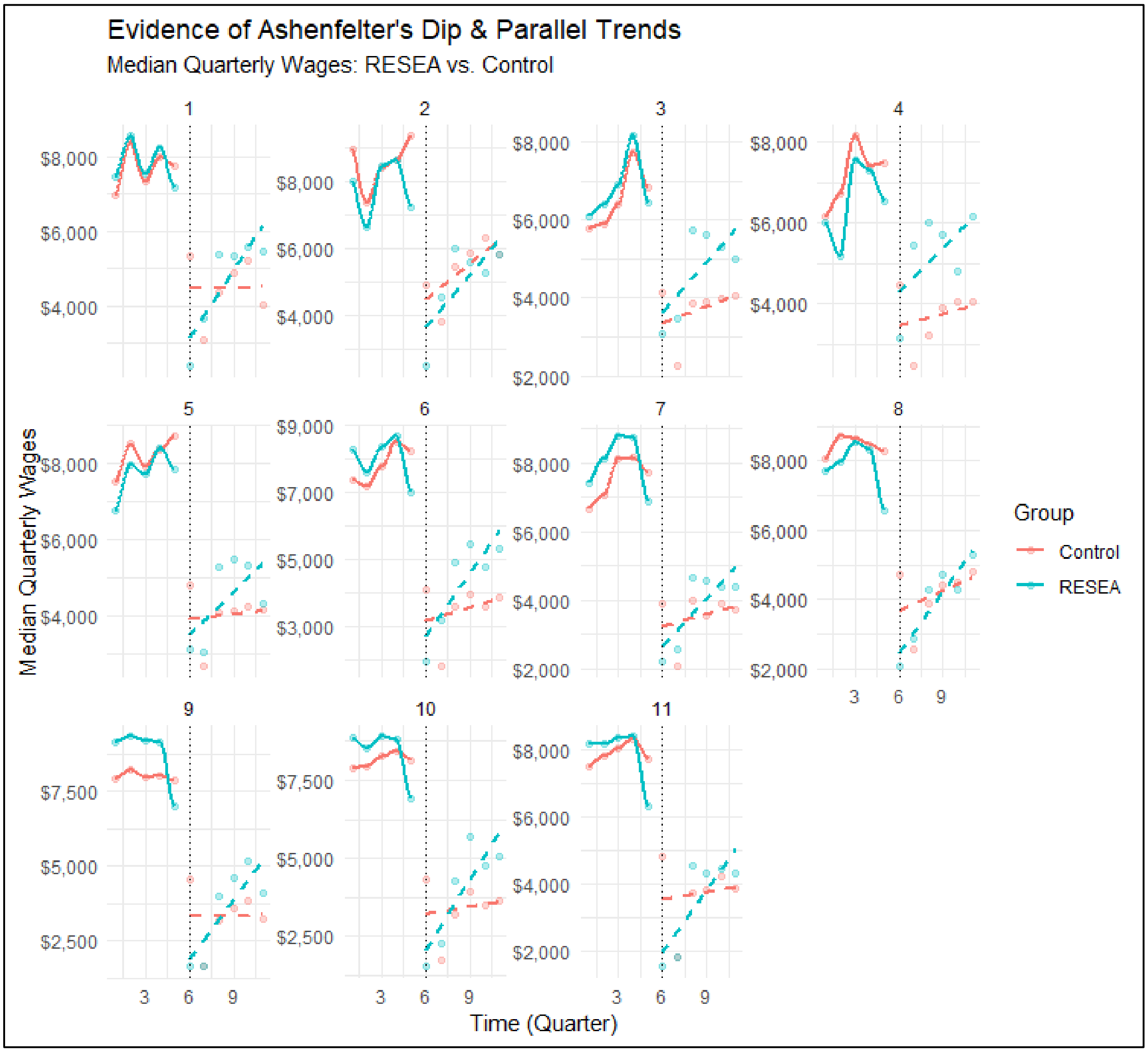


Figure 2 Data Integration and Pre-processing Workflow

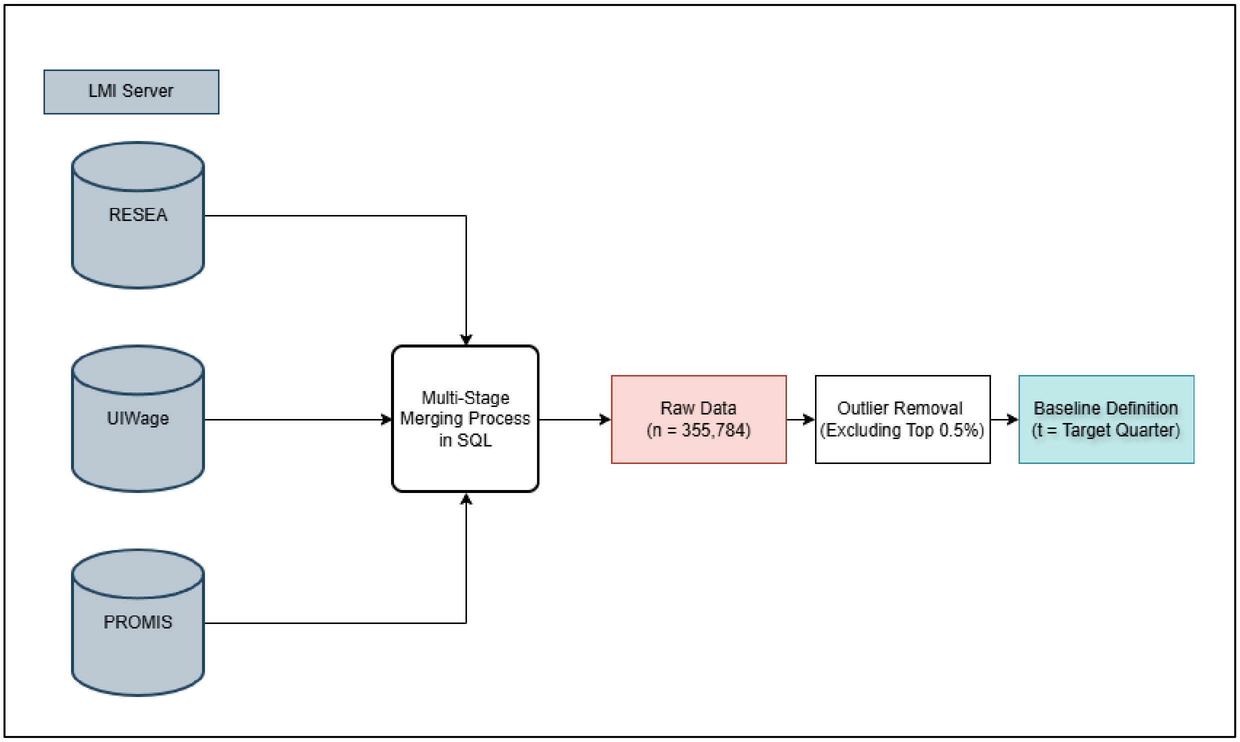


Figure 3 Covariate Balance (Love Plot)

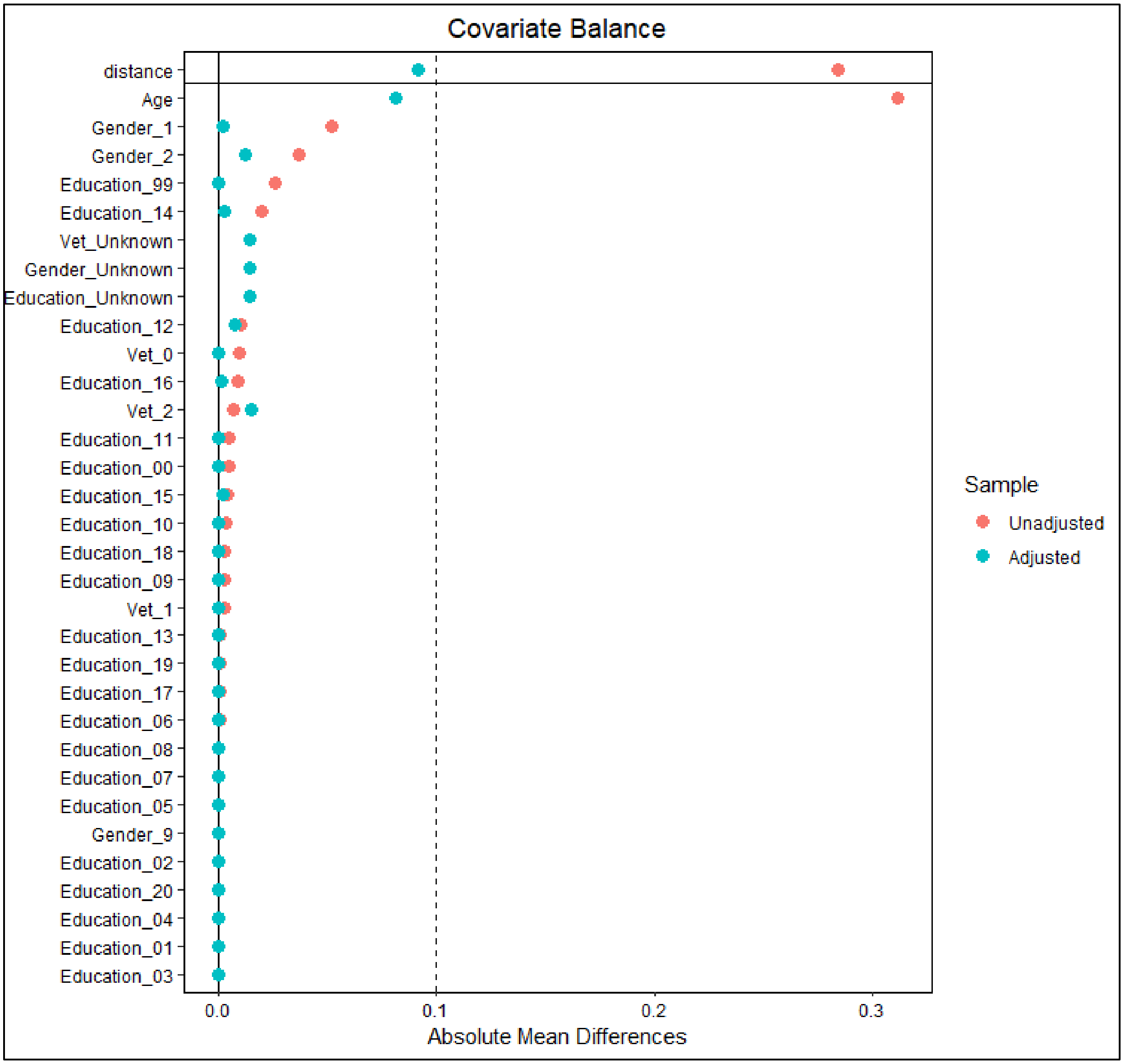


Figure 4 RESEA Impact on Unemployment Duration

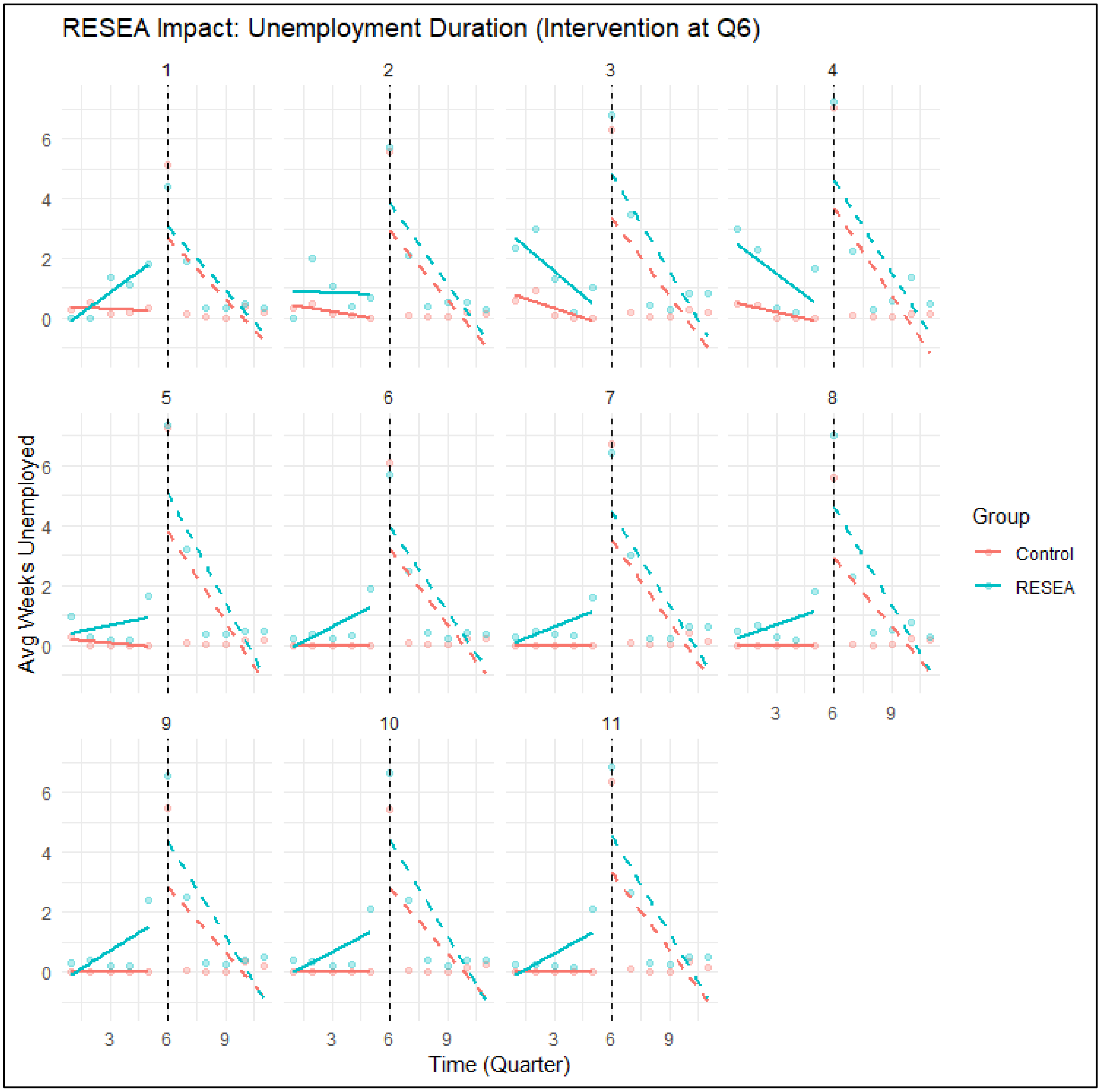
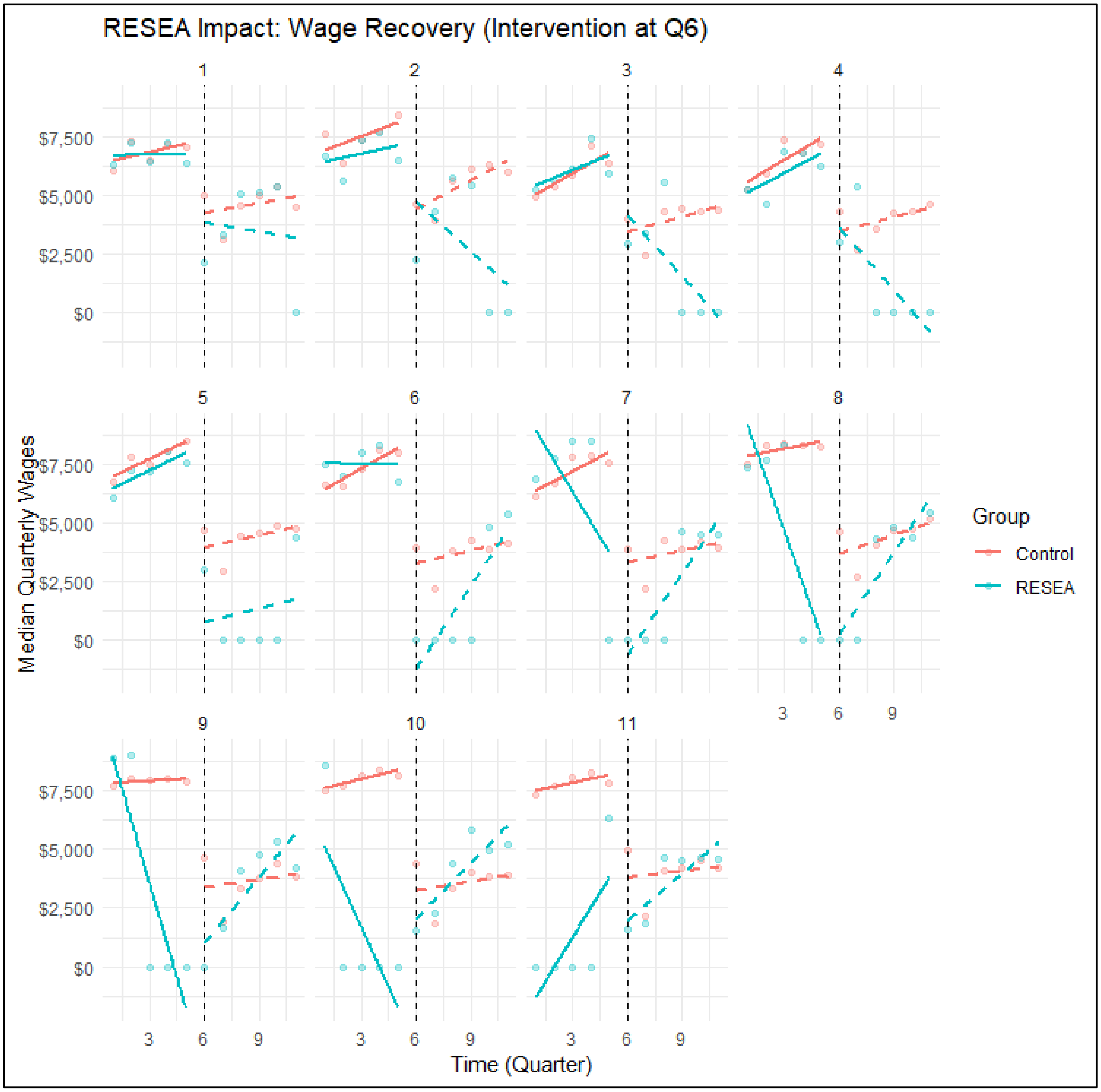


Figure 5 RESEA Impact on Median Quarterly Wage Recovery



Tables

Table 1 Cohort Distribution and Participant Grouping

Cohort Distribution and Participant Grouping					
Cohort	Intervention Quarter	Pre-Intervention Window	Post Intervention Window	RESEA	Non-RESEA
1	2021 Q4	2020 Q3 – 2021 Q3	2022 Q1 – 2023 Q1	939	1,649
2	2022 Q1	2020 Q4 – 2021 Q4	2022 Q2 – 2023 Q2	1,227	1,552
3	2022 Q2	2021 Q1 – 2022 Q1	2022 Q3 – 2023 Q3	1,095	1,474
4	2022 Q3	2021 Q2 – 2022 Q2	2022 Q4 – 2023 Q4	1,686	1,696
5	2022 Q4	2021 Q3 – 2022 Q3	2023 Q1 – 2024 Q1	493	1,479
ADOW 2023 Policy Intervention Begins					
6	2023 Q1	2021 Q4 – 2022 Q4	2023 Q2 – 2024 Q2	1,690	1,314
7	2023 Q2	2022 Q1 – 2023 Q1	2023 Q3 – 2024 Q3	1,691	1,349
8	2023 Q3	2022 Q2 – 2023 Q2	2023 Q4 – 2024 Q4	1,920	1,363
9	2023 Q4	2022 Q3 – 2023 Q3	2024 Q1 – 2025 Q1	1,568	1,320
10	2024 Q1	2022 Q4 – 2023 Q4	2024 Q2 – 2025 Q2	2,072	1,447
11	2024 Q2	2023 Q1 – 2024 Q1	2024 Q3 – 2025 Q3	1,924	1,662

Table 2 Fixed-Effects Regression Estimates: RESEA Program Impact

	Total Wages		Weeks Unemployed	
Variable	**Beta**[1]	**SE**[2]	**Beta**[1]	**SE**[2]
Post-Policy	-6,784***	125	0.30***	0.004
Time	-291***	10.9	0.16***	0.001
is_resea * Post-Policy	-1,265***	183	5.0***	0.066
is_resea * Time	-548***	15.6	0.39***	0.006
Post-Policy * Time	605***	16.6	-0.15***	0.001
is_resea * Post-Policy * Time	537***	24.2	-0.82***	0.009

[1] *p<0.05; **p<0.01; ***p<0.001

[2] SE = Standard Error

Note: Standard errors clustered by ID. Significance levels: *p<0.05, **p<0.01, ***p<0.001.

Table 3 Estimated Fiscal Savings by Cohort

Estimated Fiscal Savings[1]				
Intervention Quarter	Avg. Weekly Benefits	Savings Coefficient	RESEA	Quartlerly Savings ($)
2021 Q4	201.96	0.821	939	155,697
2022 Q1	205.31	0.821	1,227	206,826
2022 Q2	193.53	0.821	1,095	173,983
2022 Q3	197.93	0.821	1,686	273,973
2022 Q4	215.49	0.821	493	87,221
ADOW 2023 Policy Intervention Begins				
2023 Q1	210.42	0.821	1,690	291,955
2023 Q2	212.94	0.821	1,691	295,629
2023 Q3	220.27	0.821	1,920	347,214
2023 Q4	220.11	0.821	1,568	283,352
2024 Q1	225.72	0.821	2,072	383,978
2024 Q2	225.74	0.821	1,924	356,574

[1] *Estimated Fiscal Savings = RESEA Participants x Average Weekly Benefit Amount x Savings Coefficient*

Post Policy Intervention Savings (2023 Q1 - 2024 Q2)	
$	1,958,702

Appendix B

Propensity Score Matched Interrupted Time Series Model Code

B.1 Data Import and Outlier Management

We first extract the master analytic dataset and remove extreme outliers (top 0.5% of wage earners) to ensure that the propensity score matching is not biased by anomalous income observations.

```
# Extract master data from SQL
query <- "select * from [RESEA].[dbo].[ITS_Master_Final_Clean]"
master_data <- dbGetQuery(con, query)

#Remove top 0.5% wage outliers to ensure model stability
id_stats <- master_data %>%
  group_by(ID) %>%
  summarize(
    avg_wage = mean(total_quarterly_wages, na.rm = TRUE),
    max_wage = max(total_quarterly_wages, na.rm = TRUE))

outlier_ids <- id_stats %>%
  filter(max_wage > quantile(max_wage, 0.995)) %>%
  pull(ID)

master_data <- master_data %>% filter(!ID %in% outlier_ids)
```

B.2 Propensity Score Matching (PSM)

To construct a valid counterfactual, we match RESEA participants with non-participants based on age, education,gender, and veteran status using nearest-neighbor matching(1:1).

```
#Define the baseline population
baseline <- master_data %>%
  filter(Time == 'target') %>%
  dplyr::select(ID,quarter, is_resea, Age, Education, Gender, Vet)

# 1:1 Nearest Neighbor Matching
m_out <- matchit(is_resea ~ Age + Education + Gender + Vet ,
         data = baseline,
         method = "nearest",
         ratio = 1)

# Retain only matched subjects across all 21 study quarters
matched_baseline <- match.data(m_out)
final_analysis_data <- master_data %>%
  filter(ID %in% matched_baseline$ID)
```

B.3 Variable Build and Inflation Adjustment

We map the temporal periods to a numeric scale and adjust quarterly wages for inflation using the CPI-U index (2023) to allow for accurate longitudinal wage comparisons.

```
#Map time periods to numeric periods
time_map <- c("pre_5" = 1, "pre_4" = 2, "pre_3" = 3,
        "pre_2" = 4, "pre_1" = 5, "target" = 6,
        "post_1" = 7, "post_2" = 8, "post_3" = 9,
        "post_4" = 10, "post_5" = 11)
```

```
final_analysis_data <- final_analysis_data %>%
  mutate(time_numeric = time_map[Time])

# Map CPI and merge it into the final dataset
final_analysis_data <- final_analysis_data %>%
  mutate(is_post_policy = ifelse(time_numeric > 6, 1, 0))
cpi_mapping <- data.frame(
  quarter = c("20203", "20204", "20211", "20212", "20213",
              "20214", "20221", "20222", "20223", "20224",
              "20231", "20232", "20233", "20234", "20241",
              "20242", "20243", "20244", "20251", "20252",
              "20253"), # List your quarters
  cpi_value = c(259.767, 260.364, 263.158, 269.315, 273.627,
               277.780, 284.123, 292.572, 296.418, 297.507,
               300.615, 304.2, 306.835, 307.156, 310.358,
               313.931, 314.879, 315.587, 318.851, 321.607,
               323.941)   # List corresponding CPI-U values
)
cpi_2023_avg <- mean(c(300.615, 304.2, 306.835, 307.156))


final_analysis_data <- final_analysis_data %>%
  left_join(cpi_mapping, by = "quarter") %>%
  mutate(real_quarterly_wages = total_quarterly_wages * (cpi_2023_avg / cpi_value))
```

B.4 Econometric Triple-Difference (DDD) Estimation

The impact of the RESEA program is estimated using a fixed-effects model, clustering standard errors at the individual claimant level to account for intra-personal correlation over time.

```
# Impact on Wages
wage_model <- feols(real_quarterly_wages ~ is_resea * is_post_policy * time_numeric +
                     factor(Cohort) | ID,
                   data = final_analysis_data, cluster = ~ID)
```

```
The variables 'is_resea', 'factor(Cohort)2' and nine others have been removed because of collinearity (see $collin.var).
```

```
# Impact on Unemployment Duration
weeks_model <- feols(num_weeks_unemployed ~ is_resea * is_post_policy * time_numeric +
                      factor(Cohort) | ID,
                    data = final_analysis_data, cluster = ~ID)
```

```
The variables 'is_resea', 'factor(Cohort)2' and nine others have been removed because of collinearity (see $collin.var).
```

```
# View summary results
summary(wage_model)
```

```
OLS estimation, Dep. Var.: real_quarterly_wages
Observations: 358,710
Fixed-effects: ID: 32,610
Standard-errors: Clustered (ID)
                                    Estimate Std. Error   t value   Pr(>|t|)
is_post_policy                     -6784.304   124.7675 -54.37556  < 2.2e-16
time_numeric                        -291.281    10.9486 -26.60434  < 2.2e-16
is_resea:is_post_policy            -1265.066   182.6632  -6.92567 4.4195e-12
is_resea:time_numeric               -548.408    15.5619 -35.24050  < 2.2e-16
is_post_policy:time_numeric          605.152    16.5515  36.56178  < 2.2e-16
is_resea:is_post_policy:time_numeric 536.785    24.1618  22.21622  < 2.2e-16
```

```
is_post_policy                    ***
time_numeric                      ***
is_resea:is_post_policy           ***
is_resea:time_numeric             ***
is_post_policy:time_numeric       ***
is_resea:is_post_policy:time_numeric ***
... 11 variables were removed because of collinearity (is_resea, factor(Cohort)2 and 9 others [full set in $collin.var])
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 4,839.5     Adj. R2: 0.542232
              Within R2: 0.096253
```

```r
summary(weeks_model)
```

```
OLS estimation, Dep. Var.: num_weeks_unemployed
Observations: 358,710
Fixed-effects: ID: 32,610
Standard-errors: Clustered (ID)
                                      Estimate Std. Error   t value  Pr(>|t|)
is_post_policy                        0.298504   0.004391   67.9804 < 2.2e-16
time_numeric                          0.162239   0.000607  267.3272 < 2.2e-16
is_resea:is_post_policy               5.038095   0.065585   76.8178 < 2.2e-16
is_resea:time_numeric                 0.388256   0.005928   65.4959 < 2.2e-16
is_post_policy:time_numeric          -0.154420   0.000737 -209.4464 < 2.2e-16
is_resea:is_post_policy:time_numeric -0.821387   0.008627  -95.2079 < 2.2e-16

is_post_policy                    ***
time_numeric                      ***
is_resea:is_post_policy           ***
is_resea:time_numeric             ***
is_post_policy:time_numeric       ***
is_resea:is_post_policy:time_numeric ***
... 11 variables were removed because of collinearity (is_resea, factor(Cohort)2 and 9 others [full set in $collin.var])
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 1.58976     Adj. R2: 0.187271
              Within R2: 0.127947
```

Appendix C

Raw Data Dictionary		
Variable name	Data Type	Description
ID	Integer	Unique Identifier for claimants in the study.
Cohort	Numeric	Identifier for the 11 distinct intervention groups based on quarter of entry.
Quarter	String	The calendar quarter associated with the observation.
Time	String	The categorical temporal position relative to intervention.
Time_Numeric	Integer	Numerical mapping of Time from 1 to 11, where 5 represents the target intervention quarter.
is_resea	Binary (0/1)	Indicator of RESEA program participation (1 = Participant, 0 = Control).
Age	Integer	The age of the claimant at the time of the claim.
Educaiton	Categorical	Highest level of educational attainment.
Gender	Categorical	The claimant's gender.
Vet	Categorical	Veteran status of claimant.
total_quarterly_wages	Numeric	Total gross wages reported for the quarter.
num_weeks_unemployed	Integer	Total count of certified weeks of unemployment within the quarter.

Final Model Data Dictionary		
Variable Name	Data Type	Description
ID	integer	Unique identifier for each claimant
is_resea	Binary (0/1)	Indicator of RESEA Program Participation.
real_quarterly_wages	Numeric	Total Quarterly Wages adjusted to 2023 constant dollars.
num_weeks_unemployed	integer	Total count of certified weeks of unemployment.
Time_Numeric	integer	Mapping of quarterly periods 1 through 11.