Unemployment Insurance Policy: The Impact of Required Reemployment Service and Eligibility Assessment Programs on Worker Outcomes

Elizabeth Llanes

November 13, 2024

The most recent version of this paper is available at Link[1]

Abstract: This paper studies the impact of required reemployment service and eligibility assessment programs within unemployment insurance (UI) policy. Using the Current Population Survey Displaced Worker Supplement, I conduct a difference-in-differences analysis of the Reemployment and Eligibility Assessment (REA) Program in the United States between 2005 and 2015. States can flexibly tailor this program, and I construct novel state-level measures that proxy for how states run their REA programs. I find that broader integration of the program within unemployment insurance policy, being stricter with assessment, and requiring more job service usage has a positive effect on earnings. Additionally, broader integration and stricter assessment decrease the weeks unemployed. Using principal component analysis, I also construct a measure of overall program rigor, and I find that more rigorous programs lead to increases in earnings and decreases in duration unemployed. I then develop a job search model incorporating features of reemployment service and assessment programs, and I use this model to understand how counterfactual UI policy design affects welfare, spending, access to unemployment insurance, and the unemployment rate. I find that both expanding the program and increasing disqualification strictness leads to decreases in the unemployment rate at the expense of spending, overall welfare, and access. Additionally, it disproportionally has negative effects on low-skill workers. I also find that decreasing the replacement rate by five percentage points has similar effects on the unemployment rate and decreases spending. However, it would result in welfare declines for both high- and low-skilled workers.

[1] The paper can also be accessed at `https://users.ssc.wisc.edu/~llanes/LlanesJMP.pdf`

*Thanks to Jeff Smith, Naoki Aizawa, Corina Mommaerts, Matt Wiswall, and participants at MEA, APPAM and in the UW-Madison Public Student Seminar and Labor Reading Group for providing helpful comments.

1 Introduction

In practice, Unemployment Insurance policy is incredibly complex and has many design features. However, in the economics literature much of the focus is on benefit levels, replacement rates, and potential benefit duration. One feature of UI policy is requirements to continue to be eligible for UI while already receiving payments. In my paper, I examine requirements to participate in reemployment services and additional eligibility assessment in order to keep receiving payments.

In particular, I examine these requirements using both design-based and modeling methods. I conduct a difference-in-differences analysis of the implementation of the Reemployment and Eligibility Assessment (REA) Program in the United States to examine whether how states ran their programs affected worker outcomes. Additionally, I develop a model incorporating features of reemployment service and eligibility assessment programs, and I use this model to understand welfare, cost, unemployment rates, and access to unemployment insurance.

States with REA programs can select a subset of those on UI to be required to participate in an additional eligibility assessment and job service orientation meeting. With this, workers can be disqualified for not reporting to the meeting, can be disqualified or found to be receiving too high of payments through the meeting, or can be required to participate in even additional job services. States have flexibility in who they choose to target, how strict they are, and what additional services they require. This led to variation in REA programs across the United States.

The design of REA is intended to address issues in the unemployment literature and policy. For instance, the government would like to provide benefits to those who need them, but there is asymmetric information. Additional eligibility meetings can help caseworkers learn additional information about the worker. Also, hassle costs may drive individuals who do not actually need the benefits to choose to no longer collect UI benefits. Additionally, eligibility assessment meetings after starting to receive UI can allow caseworkers to examine whether the individual is meeting the active requirements to keep receiving UI. Finally, considering broader unemployment policy-if there are search frictions, including worker information frictions, these programs can help the planner intervene. Job services exist to help match workers and firms. Additional job search services can help workers gain job search human capital.

I construct novel measures to understand how states are actually implementing these programs. Using these proxy measures on how states implemented their REA programs, I find that how states run their reemployment service and eligibility assessment programs matters. I find that broader integration of the program within UI policy, being stricter with assessment, and requiring more job service usage has a positive effect on earnings after a job loss. Additionally, broader integration and stricter assessment decreases the weeks unemployed. Using Principal Component Analysis to construct an alternate measure of program implementation, I find that more rigorous programs increase earnings and decrease weeks unemployed.

The first part of the paper indicates that these programs can be designed and implemented in a manner that is beneficial for certain worker outcomes. In the second part of the paper, I further explore the balance of the potential costs and benefits of the program. Costs of the program include direct spending and decreases in access to UI. To do this, I develop a job search model incorporating program drop out due to hassle costs, potential UI disqualification (dependent on ineligibility and the policymakers choice to enforce) and potential benefits of the program. I run counterfactual policy experiments varying the share of different types of workers who must participate, disqualification strictness for eligibility issues found, and varying the replacement rate. I find that increasing participation requirements and/or eligibility enforcement lead to increases in costs, decreases in the unemployment rate, and increases overall welfare at the expense of decreasing access to UI. I find that decreasing UI replacement rates can lead to similar decreases in unemployment rates but it decreases overall welfare.

In the remainder of this paper, I will first discuss my contribution to the literature. Then I will describe my data and provide background on the policy. Then I will present my design-based empirical strategy and show my results. Next I will discuss my model and baseline calibration. Then, I will present the alternate policy design results. Finally, I will conclude.

2 Literature

I contribute to several strands of the literature. Broadly, I contribute to the literature on optimal UI policy. Baily (1978) and Chetty (2006) provide the groundwork for much of this analysis. A major focus of this literature is balancing the labor distortion costs of UI with the consumption smoothing benefits (see for example Moffitt (1985), Gruber (1997), Browning and Crossley (2001), and Chetty (2006)). I will model characteristics of reemployment service and assessment programs and will be able to discuss how these programs fit into UI.

I also contribute to the literature on the effects of UI on post-unemployment earnings. The empirical literature on the effect of unemployment insurance potential duration and monetary generosity has been mixed and the differing results are still not fully understood (Addison and Blackburn (2000); Centeno (2004); Card, Chetty, and Weber (2007); van Ours and Vodopivec (2008); Caliendo, Tatsiramos, and Uhlendorff (2009);Nekoei and Weber (2017)). In this paper, I examine whether REA programs within UI affect post-unemployment earnings. If this UI feature is important and is often ignored, it can potentially explain some of the differences in the results.

I closely add to the literature on the program evaluation of reemployment services and assessment programs (see for instance Black, Galdo, and Smith (2007), Poe-Yamagata et al. (2011), Michaelides, Poe-Yamagata, et al. (2012), Michaelides and Mueser (2018), Klerman et al. (2019), Michaelides, Mueser, and Smith (2021), Manoli, Michaelides, and Patel (2023), and Pepin et al. (2023)). These studies find null, modestly, or substantially positive effects on earnings and employment. They also find null or decreases in UI duration. This literature focuses on a small subset of states, and states differ in their implementation of the program which could lead to differing results. I contribute by adding a national level analysis of the roll-out of the REA program. I also provide a comparative analysis of how states across the country are implementing the program and whether that affects worker outcomes. This can help us understand the external validity of these studies, heterogeneity of implementation, and what is leading to differing results. My model can also incorporate the findings from these studies, and I can examine alternate policy design and welfare.

I also closely add to the literature incorporating job services and monitoring into structural models. This includes studies in the context of Europe including Cockx et al. (2018) [Belgium], Berg and Klaauw (2006) [Netherlands], Maibom (2023) and Gautier et al. (2018) [Denmark], Fougère, Pradel, and Roger (2009) [France] and Wunsch (2013) [Germany]. European UI policy is typically more generous, provides a longer duration of benefits, and has interventions at a later stage. I add to this by modeling a unique UI policy environment in which there is an early intervention of additional eligibility assessment and reemployment services in the context of the United States. Plesca (2010) and Pavoni and Violante (2007) model different policies in the context of the US. Lawson (2023)examines optimal unemployment policy in the US that could include job services and job service monitoring generally. However, the study focuses on a time before the expansion of reemployment service and eligibility assessment programs in the US and does not incorporate findings from these programs. This is ultimately the focus of my analysis.

3 Data

3.1 Individual Level Data

My primary individual level data set is the Displaced Worker Supplement (DWS) from the Integrated Public Use Microdata Series (IPUMS). The DWS is a supplement to the basic monthly Current Population Survey (CPS), and I additionally use the data from the basic monthly CPS conducted in the same month as the DWS. The Displaced Worker Supplement has been administered every other year since 1984 to individuals who were displaced from a job. This survey contains key information for my analysis including demographics, UI benefit receipt, duration unemployed, state-level geography, and details on the current and lost job.

This paper utilizes data from the 2006 to 2018 displaced worker supplements. I examine the experiences of workers aged 25 to 61. I limit the sample to age 61 to avoid complications with retirement decisions once individuals become eligible for social security at 62. I drop individuals missing essential demographic, occupation, or UI data. Additionally, across survey years, the definition of a displaced worker changes. So in order to construct my sample, I restrict my sample to those meeting a consistent definition of a displaced worker: individuals who lost their job one to three years prior, who lost their job due to layoffs or shutdowns, and who were not self-employed. Additionally, only individuals who receive UI payments are required to do these programs. So I restrict the sample to those who report receiving benefits. To get a consistent sample across states, I also restrict the sample to workers who worked full time on the lost job (in some states part-time workers are not eligible to receive UI).

Table 1 reports summary statistics for the primary sample. The reported summary statistics use survey weights. 28% of the sample is college educated. Around 80% of the sample is white, and 40% of the sample is female. The average age is around 43, and a little under 40% of workers lost a blue collar job. Additionally, the average real weekly earnings on the lost job is around $965. Individuals are unemployed on average 24 weeks, and current weekly earnings are around $415 unconditional on employment and $809 conditional on being employed.

Table 1: Displaced Worker Supplement Summary Statistics

	Mean	SD
College	0.28	0.45
White	0.79	0.41
Female	0.4	0.49
Age	43.29	10.26
Wkly. Earnings, Lost Job	964.48	601.12
Blue Collar, Lost Job	0.37	0.48
Married	0.56	0.5
Current Wkly. Earnings	415.86	591.83
Current Wkly. Earnings, Employed	808.53	606.15
Weeks Unemployed	23.67	23.55

This table reports summary statistics for workers who lost a full-time job in the Displaced Worker Supplement, 2005-2015. Survey weights are used.

3.2 Policy Data and Economic Conditions

I obtain information on REA policy from the Department of Labor Employment Training Administration "Reemployment Services and Eligibility Assessment Workload" report and data (ETA report 9128). From this data, I have state-level quarterly data on overall REA program participation, service and training usage, UI over-payments found during assessments, and UI disqualifications resulting from the program. I use this information along with data from ETA Claims and Payment Activities report (ETA 5159) to construct measures of usage/over-payments/disqualifications as a fraction of individuals participating in the state UI system. I focus on fractions with state first UI payments in the denominator (individuals learn about participation requirements shortly after receiving their first

UI payment). I also use data from the American Community Survey on characteristics of individuals unemployed in each state to construct robustness measures. In my empirical strategy, I use these measures to analyze the extensive margin of the introduction of REA and the intensive margin of how states run their programs. I discuss the alternate proxy measures for REA implementation further in the empirical strategy section of the paper.

In my analysis, I also control for UI benefit amount generosity. I follow the literature in using the maximum benefit amount as a proxy for this generosity (see for instance Chetty (2008) and Hsu, Matsa, and Melzer (2018)). In particular, I use yearly state-level measures of the Real Maximum Benefit=Real Maximum Weekly Benefit*Maximum Potential Week Duration. I collect this measure using the Department of Labor's publication "Significant Provisions of State UI Laws" and replication data from Hsu, Matsa, and Melzer (2018) and Kuka (2020).

Additionally, I control for state-level economic conditions. I use the Current Population survey to construct state-level measures of the real average weekly wage and unemployment rate. I also utilize Bureau of Economic analysis data on GDP per capita by state. To control for inflation, I use CPI data from the BLS and the Federal Reserve Bank of Minneapolis.

4 Policy Background

The Reemployment and Eligibility Assessment (REA) Program is an optional program for states that began in 2005. The Department of Labor provides grants to support these programs. States can also use additional funding sources to expand what the program provides. The intent of the program is to reduce total unemployment insurance paid. To do this, the program has two distinct sides. The first ("carrot") side aims to provide assistance through services to help individuals find a job faster and/or find a better job match.

The second ("stick") side aims to enforce unemployment insurance rules on eligibility and payments and creates hassle costs to keep receiving unemployment insurance.

The REA program is one of three major reemployment service and assessment programs in the United States in the past thirty years. The other two programs are the Worker Profiling and Reemployment Services (WPRS) program and the Reemployment Services and Eligibility Assessment (RESEA) program. The WPRS program is a required program that began in 1994 that aims to provide job search services to workers most likely to exhaust their benefits, and focuses on services. The REA program, on the other hand, targets a wider array of participants and emphasizes both services and eligibility assessment. The RESEA program largely re-branded (with some modifications) the REA program in 2016, and in some states, incorporated the WPRS program as well. Due to the changes in 2016 and due to the disruptions with the programs during the pandemic, I focus my analysis here on 2005-2015.

The REA program fits within a state's broader UI system. After losing a job, individuals can apply to receive unemployment insurance. Workers who are deemed eligible will then receive their first payment and will continue to receive payments as long as they continue to meet the active requirements to keep UI. Initial eligibility requirements typically include reason for job loss (not the individual's fault with some exceptions) and minimum prior earnings and employment. Active requirements include job search and participation in required programs, such as the REA program.

States that have opted to have REA programs choose a subset of individuals on UI to be required to participate in the program in order to keep UI. The selection process varies by state, but the majority of states use profiling models on likelihood of benefit exhaustion.[2] After the individuals are chosen, federal requirements dictate these individuals

[2]In 2007, the Department of Labor recommended including the following independent variables: education, job tenure, industry, occupation, and unemployment rate. During this time period, states also used other methods such as random assignment or administering surveys aimed to identify those who may struggle

must participate in an initial in-person meeting which includes some form of UI eligibility and benefit payment assessment and an orientation to job services. From this initial meeting, the case worker can also require that the UI claimant attend additional assessment meetings or job services in order to keep receiving UI. States vary substantially on how they implement these programs.

The Department of Labor started the optional program in 2005, and ultimately, every state and DC participated in at least one year. However, some states chose to drop out. In 2015, the grant funding grew to $80 million to be used by 44 states and Washington DC. Although states vary in how much they spend per meeting, a typical first meeting costs around $100 (Klerman et al. (2019)). In 2022, RESEA, the successor program to REA, received $189 million in federal funding, and 49 states and DC participated in the program.[3]

As mentioned before, states are given flexibility in how they run these programs. Using the data states reported to the DOL, I will describe variation in how states have chosen to implement their programs over time. In the following table and four figures, I report usage and disqualification rates. I have quarterly data on REA usage and REA associated disqualifications. I divide these measures by that quarter's number of first UI payments. This is because the individual's initial interaction with the REA program typically happens shortly after the first payment. I then take the average over the year for each state. Table 2 reports the results for states and years with the REA program. In the appendix, Appendix Table 1 reports summary statistics for all states, including states without the program.

In Figure 1 and Table 2, I report the number of first appointments scheduled for REA as a share of the first payments. This measure provides the best estimate of how widely the program is integrated within UI policy and how the state intends to target the UI population to be in the REA program. As can be seen in Table 2, the interquartile range of the share

with finding a job

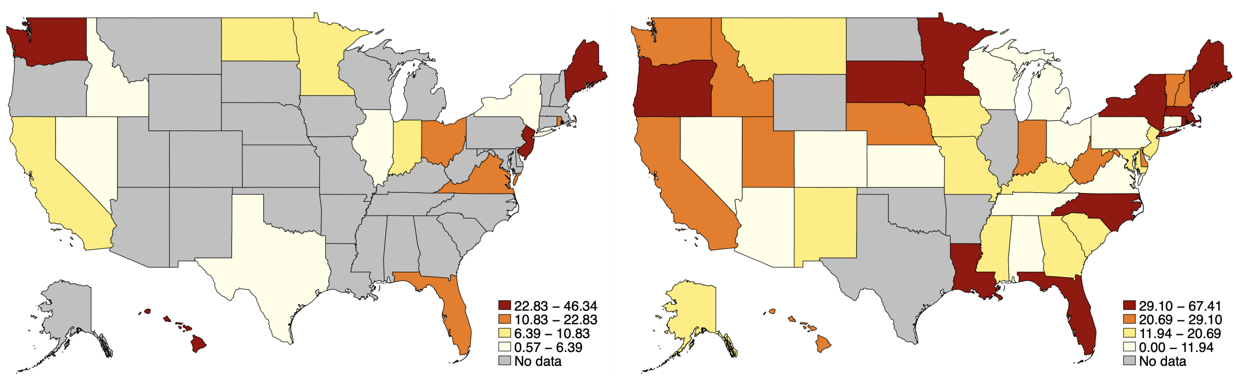
[3] North Dakota was the only state not participating in 2022.

Table 2: REA Participation and Disqualification Measures as a Fraction of First Payments, States and Years with Data

	p25	p50	mean	p75	SD
% First scheduled meetings	7.10	12.09	16.41	21.50	14.26
% Completed meetings	5.80	9.82	15.75	20.17	15.00
% Disqualified due to not reporting	0.13	0.58	1.69	2.08	2.82
% Reemployment services or training	3.81	7.77	11.72	16.35	12.14
% REA meeting resulted in disqualification or overpayment	0.07	0.28	1.10	0.76	2.70

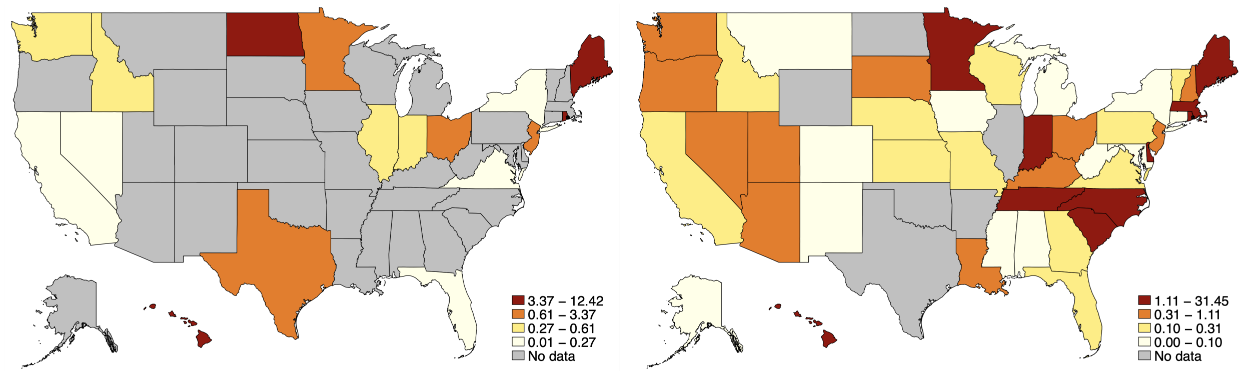
Quarterly data is from DOL ETA reports. Data is from 2005-2015. Statistics are for states and years with reported measures

Figure 1: Mean Quarterly First REA Appointtments Scheduled/First UI Payments, by State and Year



This figure shows how broad the program was over time. DOL data was used to calculate these measures. Left Map: 2006, Right Map: 2015

Figure 2: Mean Quarterly Determine Disqualified or Overpaid in Meeting/First UI Payments, by State and Year



This figure shows an aspect of strictness. DOL data was used to calculate these measures. Left Map: 2006, Right Map: 2015

of first scheduled meetings to first payments is around 7 to 21.5%. However, in Figure 1, we can see that the program is growing over time.

Figure 3 shows disqualifications due to not reporting to the meeting as a share of first payments and Figure 2 shows disqualifications or overpayments found out during REA meetings. This "stick" component of REA is generally quite low, falling under 5% for either reason for almost all states.

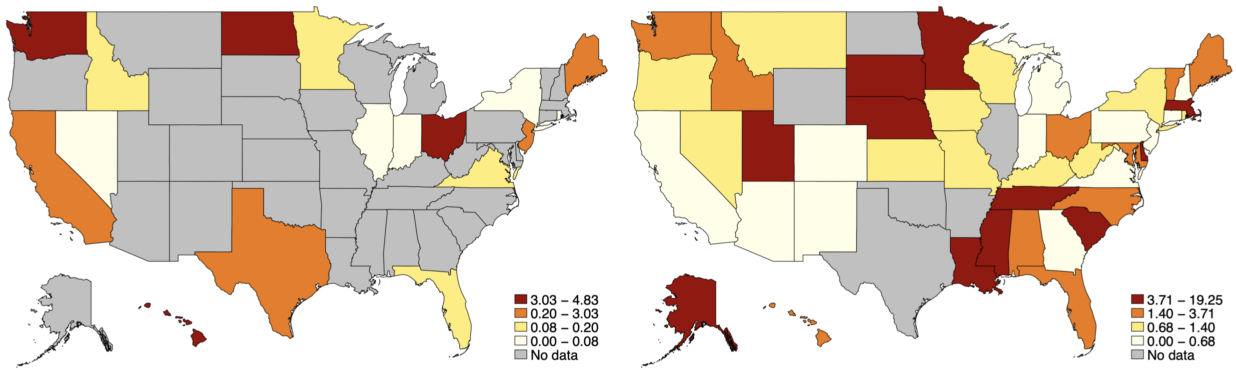
Table 2 reports the average share of job services completed/first payments [4] is 11.7% during the period of 2005 to 2015. As can be seen in Figure 4, this increases over time.

5 Empirical Strategy

In this section, I explore how implementation affects worker outcomes. The primary empirical specification is

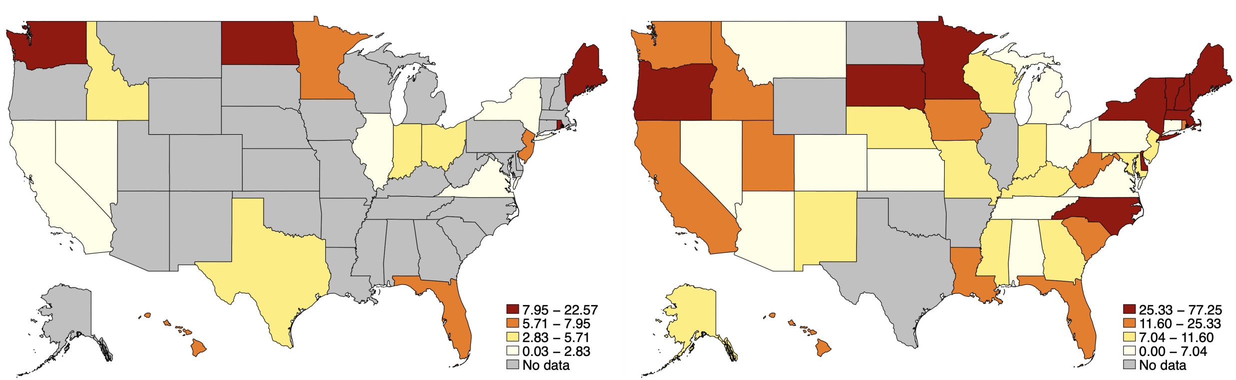
[4]Use of multiple services by one individual increases the numerator.

Figure 3: Mean Quarterly Disqualified due to Not Reporting/First UI Payments, by State and Year



This figure shows an aspect of strictness. DOL data was used to calculate these measures. Left Map: 2006, Right Map: 2015

Figure 4: Mean Quarterly Job Services or Training Usage/First UI Payments, by State and Year



This figure illustrates the service aspect of the program. DOL data was used to calculate these measures. Left Map: 2006, Right Map: 2015

$$y_{ist+1} = \beta_0 + \beta_1 P_{st} + \beta_2 X_{it} + \beta_3 Z_{st} + FE_s + FE_t + u_{ist} \tag{1}$$

In this regression i is the individual, s is the state, and t is time. Additionally, y_{ist+1} is the outcome of interest (Earnings or Weeks Unemployed), X_{it} is a vector of individual characteristics (age, age^2, weekly earnings on the lost job, and indicators for college plus, white, lost a blue collar job, married, and female), Z_{st} is a vector of state characteristics (real maximum UI benefit, state population unemployment rate, real GDP per capita, and real average weekly earnings), and u_{ist} is the error. I also include state fixed effects (FE_s) and year fixed effects (FE_t). I cluster standard errors at the state level and use survey weights in the regressions. In this regression, P_{st} is the intensive margin treatment variable. I unfortunately do not know which workers in the Displaced Worker Supplement receive the treatment. This analysis is therefore necessarily about the intent to treat. For the intensive margin analysis, I construct alternate treatment measures. For the baseline measures, I construct state-level measures of the form:

$$\frac{\text{Quarterly REA Implementation Measure}}{\text{Quarterly First UI Payments}} \tag{2}$$

In the denominator, I consistently use First UI payments. Individuals typically are exposed to the program shortly after receiving their first UI payment. I use five REA Implementation Measures in the numerator to understand different aspects of REA implementation.

The first measure is the number of first scheduled appointments. This is a proxy for how widely the program is integrated into state UI policy. Some states intend to target the majority of UI claimants, whereas other states only intend to target and interact with a specific subset. The second number is the number of completed appointments, which has a similar interpretation.

The last three measures proxy for whether states approach the policy with a "stick" or "carrot" approach[5]. I use two disqualification measures. The first disqualification measure is the number of individuals who are disqualified due to not reporting to the required meeting. The second measure is whether during the REA meeting an issue was found that resulted in either disqualification or overpayment issue. The final measure, is the proxy for the "carrot" side of the policy, which tries to help workers increase either job search human capital through job search services or general human capital through broader training. I have the number of services or trainings that are completed that are connected to the REA program[6].

Ultimately, I am interested in β_1. This represents the effect associated with a 1 percentage point increase in the share of $\frac{\text{Quarterly REA Implementation Measure}}{\text{Quarterly First Payments}}$.

5.1 Residual Measures

One may be concerned that transitory changes in the composition of the unemployed and the unemployment rate across states are driving differences in the measures and selection into the program. If that is the case, my treatment measures may reflect this, rather than proxy for how the state is implementing the policy. I therefore construct residual measures of policy implementation. To do this, I run the following regression:

$$P_{st} = \beta_0 + \beta_1 College_{st} + \beta_2 Industry_{st} + \beta_3 Occupation_{st} + \beta_4 UR_{st} + FE_s + FE_t + u_{st} \quad (3)$$

In this regression, P_{st} is one of the five $\frac{\text{Quarterly REA Implementation Measure}}{\text{Quarterly First Payments}}$ measures. The subscript s is for the state, and the subscript t is for the time. College is the share of the

[5]There is a correlation of 0.2 between the disqualification and service measures

[6]The measure can include single use of services by an individual or multiple use of services

unemployed who have a bachelor's or higher. Industry is a vector of the shares of unemployed made up of individuals from different industries. Occupation is a vector of the shares of unemployed made up of individuals from different occupations. UR is the unemployment rate. FE_s and FE_t are state and time fixed effects. Finally, u_{st} is the error. Regression Results including only states and times with REA programs and results including all states and times regardless of having a program are reported in Appendix Table 2 and 3.

I then take the difference between the actual P_{st} and the estimated $\hat{P}_{st}$ to get the residual. I then use the residuals as the treatments in the intensive margin regressions. Maps of the residual measures for First Appointments are included in the appendix.

5.2 Principal Component Analysis

The next portion of the intensive margin analysis addresses the concern that there may be correlation across measures, and these measures may also be correlated with other unobserved policies. Table 3 reports the correlation among the five $\frac{\text{Quarterly REA Implementation Measure}}{\text{Quarterly First Payments}}$ measures (scheduled, completed, disqualifications due to not reporting, training/services, and disqualification/overpayments found during meetings). It can be seen that there is moderate to high correlation among the different measures.

I conduct principal component analysis with four of the main $\frac{\text{Quarterly REA Implementation Measure}}{\text{Quarterly First Payments}}$ measures (scheduled, disqualification due to not reporting, training/services, and disqualification/overpayments). Here the principal component analysis is for states and times with REA programs.

As can be seen in Table 4, the first principal component explains 60% of the variation in the data. Table 5 shows how each variable is loaded onto each component. All variables

Table 3: Correlation Among Measures

Measure	Sched.	Compl.	Disq-No Report	Training/Services	Disq/Overpay-Mtg.
Scheduled	1				
Completed	0.8	1			
Disq-No Report	0.52	0.49	1		
Training/Services	0.81	0.87	0.42	1	
Disq/Overpay-Mtg.	0.42	0.37	0.22	0.26	1

This table shows the correlation among these different measures. This is calculated from DOL data.

positively contribute to the first component. I consider the first principal component to represent the overall rigor of the program, and I include this variable as a treatment in the intensive margin regressions. Figure 5 shows the measure across states in 2015.

Table 4: Principal Component Analysis-Eigenvalues and Proportion of Variation Explained by Each Component

Component	Eigenvalue	Difference	Proportion	Cumulative
1	2.39	1.57	0.6	0.6
2	0.82	0.18	0.2	0.8
3	0.63	0.46	0.16	0.96
4	0.17		0.04	1

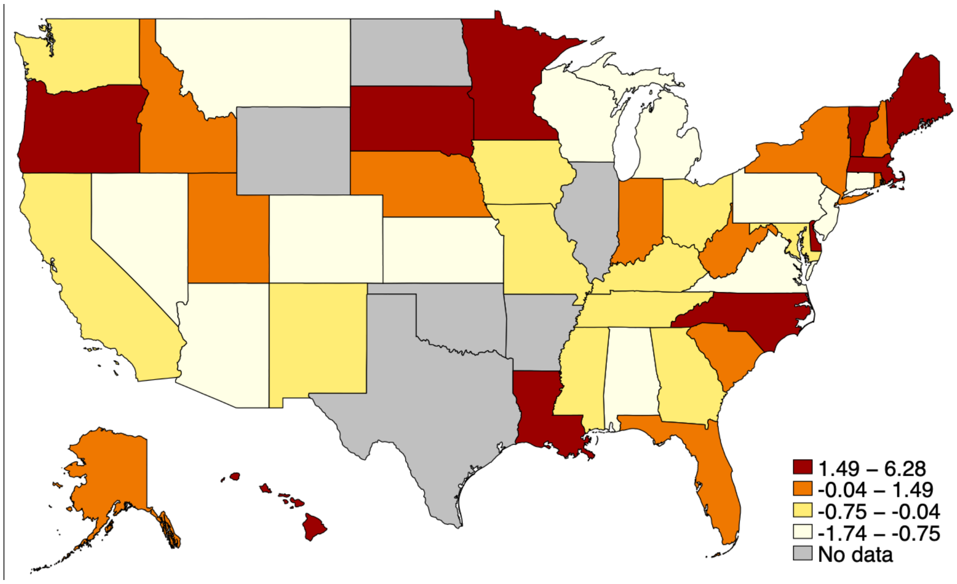
This table shows the eigenvalues and proportion of variation that is explained by each of the components. This table is calculated using DOL data.

Table 5: PCA-Eigenvectors

Variable	Comp. 1	Comp. 2	Comp. 3	Comp. 4
Scheduled	0.6	-0.07	-0.25	-0.76
Disq-No Report	0.45	-0.31	0.83	0.12
Training/Services	0.55	-0.25	-0.49	0.62
Disq/Overpay-Meeting	0.36	0.91	0.13	0.15

This table shows the eigenvectors. This is calculated using DOL data.

Figure 5: PCA Map 2015



This figure illustrates a map of the first principal component in 2015. This is calculated using DOL data.

6 Results

Table 6 reports the results for the outcome of weekly earnings one to three years after job loss. The sample included in this regression is those who have received UI and regained employment. Increases in each of the implementation measures positively affects earnings. A one percentage point increase in scheduled appointments, completed appointments, or use of reemployment services or training as a fraction of first payments increases weekly earnings by $4-$5. A one percentage point increase in disqualifications due to not reporting over First Payments increases weekly earnings by $13, and a one percentage point increase in REA meetings leading to disqualifications or payment issues over First payments increases weekly earnings by $8.5. The magnitudes are higher for the disqualification measures; however, a one percentage point increase for these measures is more substantial given the lower disqualification rates across states.

Table 7 reports the results for the outcome of weeks unemployed. A one percentage point increase in the percent of scheduled appointments to first payments deceases weeks unemployed by 0.1 weeks. A one percentage point increase in disqualifications due to not reporting as a share of first payments decreases weeks unemployed by around half a week. The signs of the coefficients for the remaining measures are also negative, but not statistically significant. The reemployment services and training measure has smallest negative value. This may make sense as some job services may help increase job search ability and help the individual gain employment faster; however, retraining or gaining more general human capital may take more time.

Table 8 reports the results for weekly earnings using the residual measures. Except for disqualification without reporting, the coefficients are slightly lower than using the implementation ratios directly. However, the overall results and interpretation is similar.

Table 9 reports the results for weeks unemployed. As with weekly earnings, coefficients are slightly lower but overall point to a similar interpretation. However, only the disqualification due to not reporting remains statistically significant.

Table 6: The Effect of REA Implementation Measure/First Payments on Weekly Earnings, Conditional on Employment

VARIABLES	(1) Wkly Earn	(2) Wkly Earn	(3) Wkly Earn	(4) Wkly Earn	(5) Wkly Earn
Scheduled	4.782***				
	(1.532)				
Completed		4.090***			
		(1.467)			
Disq., No Report			13.10***		
			(3.795)		
Train./Serv.				4.210***	
				(1.546)	
Disq./Overpay in Mtg.					8.528*
					(5.035)
Observations	2,041	2,041	2,041	2,041	2,041
R-squared	0.494	0.494	0.493	0.493	0.492

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports the results of the direct measures on earnings.

Table 7: The Effect of REA Implementation Measure/First Payments on Weeks Unemployed

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Wks Unemp.	Wks Unemp.	Wks Unemp.	Wks Unemp.	Wks Unemp.
% Scheduled	-0.131**				
	(0.0648)				
% Completed		-0.0736			
		(0.0554)			
% Disqualified, No report			-0.573***		
			(0.140)		
% Reemployment Training				-0.0515	
				(0.0513)	
% Disqualified, Overpaid					-0.347
					(0.223)
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.075	0.074	0.075	0.074	0.074

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports the results of the direct measures on weeks unemployed

Table 8: The Effect of REA Implementation Measure/First Payments on Weekly Earnings, Conditional on Employment, Residual Treatment

VARIABLES	(1) Wkly Earn	(2) Wkly Earn	(3) Wkly Earn	(4) Wkly Earn	(5) Wkly Earn
Scheduled	3.771**				
	(1.807)				
Completed		3.227*			
		(1.713)			
Disq., No Report			13.96***		
			(3.854)		
Train./Serv.				3.188*	
				(1.821)	
Disq./Overpay in Mtg.					7.724
					(5.257)
Observations	2,041	2,041	2,041	2,041	2,041
R-squared	0.493	0.493	0.493	0.493	0.492

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports the results of the residual measures on weekly earnings.

Table 9: The Effect of REA Implementation Measure/First Payments on Weeks Unemployed, Residual Treatment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Wks Unemp.	Wks Unemp.	Wks Unemp.	Wks Unemp.	Wks Unemp.
Scheduled	-0.112				
	(0.0713)				
Completed		-0.0667			
		(0.0579)			
Disq., No Report			-0.475***		
			(0.141)		
Train./Serv.				-0.0388	
				(0.0528)	
Disq./Overpay in Mtg.					-0.310
					(0.225)
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.075	0.074	0.075	0.074	0.074

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports the results on weeks unemployed. The residual measure is used.

Table 10: The Effect of REA Implementation Measure on Weekly Earnings and Duration Unemployed, PCA

VARIABLES	(1) Wkly Earn	(2) Wks Unemp.
1st Principal Component	46.40***	-1.226**
	(11.73)	(0.506)
Observations	2,041	2,298
R-squared	0.494	0.075

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports the results on weekly earnings and weeks unemployed using the first principal component measure

Finally Table 10 reports the results for the intensive margin regressions using the first principal component as the treatment. The coefficient on the first principal component is significant in both the weekly earnings regression and weeks unemployed regression. A one standard deviation (1.54) increase in the first principal component increases earnings by $71 and decreases weeks unemployed by 1.8 weeks. The rigor of the REA program affects outcomes.

Overall, this analysis indicates program implementation matters. More rigorous programs lead to increases in earnings and decreases in weeks unemployed.

7 Job Search Model with UI and Reemplyment Service and Assessment Programs

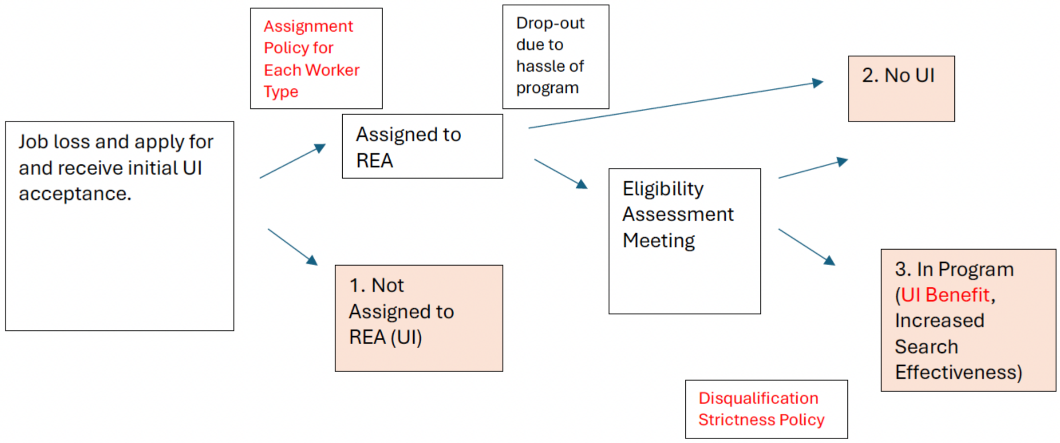
7.1 Model

More rigorous programs lead to quicker returns to work. In this section, we consider broader implications of the policy-including loss in access to UI, government spending, and welfare effects. To do this, I develop job search model that incorporates features of reemployment service and assessment programs. The model is a discrete time infinite-horizon search model. The government faces a budget constraint. Workers transition between employment and unemployment. At the start of unemployment, workers face the reemployment assessment and service system which determines how the worker will experience unemployment. This assigns them to the environment in which they will search for work. Unemployed workers choose search effort s. There are no savings, but there is home production while unemployed.

In my model, I capture key policy features from both the government policy design side and the individual's side during an unemployment spell. The government determines the share of the unemployed population who must participate in the program, disqualification strictness, and the program implementation details which affects the cost per person. From the worker's side, an individual faces potential disqualification due to eligibility issues and can also drop out of the program. Additionally, if the worker is selected into the program, the worker has an increase in search effectiveness.

The reemployment service and eligibility assessment policy is experienced immediately after job loss and receipt of the first UI payment, and it is illustrated in Figure 6. This policy determines how they will experience their unemployment spell. If a worker is not selected into the REA program, the worker can receive UI without completing services or having

Figure 6: Assignment to Unemployment Experience



This figure illustrates how individuals are assigned to their unemployment experiences. The red text shows policy decisions. The shaded boxes are the three ways in which an individual can experience unemployment

additional assessment. If the worker is selected into the REA program, the worker can drop out and not receive UI. If the worker attends the initial meeting, the worker faces a risk of disqualification. This disqualification risk is dependent on underlying UI eligibility and the government's enforcement policy. If the worker is disqualified, the worker will not receive unemployment insurance. If the worker is selected into the program but is not disqualified, they receive UI benefits and they also receive services which affects their search effectiveness.

The shaded boxes show the 3 types of unemployment experiences the worker can have while unemployed: 1. Not Assigned to REA and receive UI, 2. No UI, and 3. UI Benefits and job services which influence search effectiveness. The red text in the boxes indicate the policy details that I will change in my counterfactual policy exercises. This includes the assignment policy the government has for each type ow worker. It also includes how strict the government will be with potential UI eligibility issues. Finally, I will consider alternate UI replacement rate policies.

Employed workers receive a wage $w(h)$, where h is the skill type of the worker. They face match destruction probability δ. Additionally, they are taxed at rate τ, and have discount factor β. Their consumption is equal to $w(h)(1-\tau)$ The value function for an employed worker is:

$$V_e(h) = U(\underbrace{w(h)(1-\tau)}_{Consumption}) + \beta[\delta V_u(h) + (1-\delta)V_e(h)] \tag{4}$$

At the beginning of unemployment, the worker faces the established reemployment service and assessment policy. First, with some probability P_h, the worker is assigned to receive an assessment and service meeting with a government caseworker. Given the program implementation scheme, the government must pay c for the initial meeting. There is a drop-out rate $\alpha(h)$ specific to worker type, who choose to not attend due to the hassle of the program. With some probability d(h), the worker is actually ineligible for UI. If the worker attends a meeting, an ineligible worker's status is caught and enforced with UI disqualification with probability η. Workers who remain in the program complete services that increase search effectiveness. The value of unemployment at the start of the spell is:

$$\begin{aligned} V_{u0}(h) = (1-P) & \overbrace{V_{u,ben}(h)}^{\text{Value benefits, no program}} \\ +P(\eta d + \alpha(h)) & \overbrace{V_{u,disq}(h)}^{\text{Value if disqualified or drop out}} \\ +P(1-\eta d - \alpha(h)) & \overbrace{V_{u,pben}(h)}^{\text{Value if non-disqualified participant}} \end{aligned} \tag{5}$$

The unemployed worker ultimately searches for a job in one of the following situations: 1) Has UI benefits and did not participate in any meetings 2) Has no benefits after being disqualified during the REA meeting or dropping out 3) Has UI benefits and is required to participate in job services.

All unemployed individuals make a job search effort choice s that is subject to convex effort cost $e(s)$. Job search effectiveness is given by λ_{hm}, where h is the skill type and m is if the individual is a job service participant. The probability of finding a new job is $\lambda_{hm}s$. Unemployed workers also produce home production ψ_h

Workers who are not disqualified or drop outs receive benefit b, which is equal to the replacement rate r_h times the wage w(h).

The value function for unemployed workers with UI who had no interaction with the assessment and service program is:

$$V_{u,ben}(h) = U(b + \psi(h)) - e(s) + \beta[\lambda_h s V_e(h) + (1 - \lambda_h s) V_{u,ben}(h)] \tag{6}$$

The value function for unemployed workers without UI is:

$$V_{u,disq}(h) = U(\psi(h)) - e(s) + \beta[\lambda_h s V_e(h) + (1 - \lambda_h s) V_{u,disq}(h)] \tag{7}$$

The value function for unemployed workers with UI, who participated in the initial orientation/assessment meeting, and who are continuing to participate in services is:

$$V_{u,pben}(h) = U(b + \psi(h)) - e(s) + \beta[\lambda_{hm} s V_e(h) + (1 - \lambda_{hm} s) V_{u,pben}(h)] \tag{8}$$

The public sector has to balance the budget constraint in a given period:

$$\tau(\sum_{h_{low}}^{h_{high}} \phi(h) w(h)) = (\overbrace{u_t^b * b}^{\text{UI benefits}} + \overbrace{u_t^o * c}^{\text{Program}}) \tag{9}$$

On the revenue side of the equation, $\phi(h)$ is the share of individuals with a given skill level, and $w(h)$ is the wage given to a person with that skill level. Additionally τ is the tax rate. On the cost side of the equation, u_t^b is the share of unemployed workers receiving UI benefits and u_t^o is the share of workers who receive the initial meeting in that period. Additionally, b is the cost of the UI benefit and c is the program cost of the initial meeting.

7.2 Calibration

With this model, I would like to understand how counterfactual policies affect worker outcomes. Table 11 shows the parameters for the baseline specification. I utilize the following functions for the utility of consumption and the cost of search in my model:

$$U(c) = \frac{\mathrm{c}^{1-R} - 1}{1 - R} \tag{10}$$

$$e(s) = \frac{ln(1 - s) + s}{-\theta_h} \tag{11}$$

In this framework, a period is designated as one month, and I have two types of workers based on prior wages. I set δ (match destruction rate), β (discount factor), and R (coefficient of relative risk aversion) to match the literature. Additionally, I normalize λ_h with no meeting for both types of workers to 1. I use data from the displaced worker supplement to calculate the median pre-job loss wages and I place workers into low and high skill groups. The low skill group wage is normalized to 1 and the high skill wage is scaled accordingly. I set the level of home production to allow for 85% of normal consumption with UI for both types of workers.

7.2.1 Policy Parameters

I calibrate the policy parameters to match unemployment insurance and reemployment service and assessment policy data. The replacement rate is set to 0.42 for high skill workers and 0.50 for low skill workers based on data from DOL. The unemployment insurance benefit is calculated as the replacement rate*normal wage for the skill type.

For the share of each type in the program, I impute who among the unemployed would likely be selected into the program in each state in my period and then take an average. The imputation method incorporates data from the CPS, ACS and DOL. The Department of Labor has provided recommendations to states on how to select people into the program. I use recommended variables available in both the CPS and ACS. These include education level, occupation categories (25), industry categories (13). Using the CPS, I then run the following linear regression with an indicator of being unemployed for greater than 26 weeks as an outcome:

$$y_{it} = \beta_0 + \beta_1 BA_{it} + \beta_2 Occ_{it} + \beta_3 Ind_{it} + u_{it} \tag{12}$$

This allows me to get a general profiling model based on worker characteristics. I then use the American Community Survey data to assign a profiling score to unemployed individuals. I then match this to state-level data on the share of individuals selected into the program in each state. Given this information, I determine if an individual is likely to be selected into the program. I then take the average share across each type of worker who would likely be selected into the program.

The underlying UI ineligibility rate for each type is calculated from microdata from the Benefit Accuracy Measurement Program, which is a program that audits unemployment insurance claimants for the accuracy of their claims. In particular it checks for overpayments or underpayments among paid claims. It also provides a reason for why there is an issue. I select reasons that would likely result in a disqualification issue, and I create averages for low and high skill workers.

The REA cost is selected to be a mid-range cost from the experimental papers, and it is re-scaled to work with the wage re-scaling.

The disqualification rate is calculated using both DOL data on REA programs and BAM data. I take the overall disqualification rates calculated in the first part of the measure, and I calculate the ineligibility measure from the BAM data. The strictness of disqualification is defined as:

$$\eta = \frac{\text{Actual Disqualification Rate}}{\text{BAM Ineligibility Rate}} \tag{13}$$

Finally, I want to consider how the program may lead to individuals dropping out of the program at the expense of losing benefits. In Klerman et al. (2019), the report provides estimates on the decrease in UI weeks for below and above median wage workers. They suggest that half of this decrease comes from moving into still being unemployed but not receiving UI. I calculate drop out rates to match the expected drop in weeks.

7.2.2 Targeted Parameters

The last four parameters are calibrated to match certain moments. For the search cost parameter, I target the mean duration unemployed in the CPS Displaced Worker Supplement for below median and above median wage workers. For both types, the number of weeks unemployed is 23 and I match that target.

For the search effectiveness after program participation, I target half of the estimated

Table 11: Parameters-Baseline Specification

Name	Value	Description	Source
δ	0.0100	Match Destruction	Literature
β	0.9975	Discount Factor	Literature
R	1.75	Coefficient of Relative Risk Aversion	Literature
λ	1	Effectiveness of Job Search (No Services)	Set
w$(h = low)$	1	Wage of Low Skill Worker	Set
w$(h = high)$	2.5	Wage of Low Skill Worker	Set, Calculation CPS
$psi(h = low)$	0.35	Home Production Low Skill	Literature and Calc.
$psi(h = high)$	1.1075	Home Production High Skill	Literature and Calc.
$P(h = low)$	0.13	Share Unemployed in Program	Imputation-DOL, CPS & ACS
$P(h = high)$	0.11	Share Unemployed in Program	Imputation-DOL, CPS & ACS
r_{low}	0.5	Replacement Rate Low Skill	DOL
r_{high}	0.42	Replacement Rate High Skill	DOL
$d(h = low)$	0.09	UI Ineligibility Rate	Benefit Accuracy Measurement
$d(h = high)$	0.05	UI Ineligibility Rate	Benefit Accuracy Measurement
c	0.5	REA Cost	Scaled Cost-REA Study
η	0.2557	Disqualification Strictness	Calc-DOL REA & BAM data
$\alpha(h = low)$	0.0.0338	Drop Out Rate	Calc-REA Study
$\alpha(h = high)$	0.0202	Drop Out Rate	Calc-REA Study
λ_{hm}	1.036	Search Effectiveness Low	Target
λ_{hm}	1.02	Search Effectiveness High	Target Δ UI Weeks
$\theta(h = low)$	0.0293	Search Cost Parameter High	Target mean unemployed wks
$\theta(h = high)$	0.0409	Search Cost Parameter High	Target mean unemployed wks

This table shows the different parameters used in the baseline specification and the sources.

decrease in duration on UI benefits for below and above median workers in Klerman et al. (2019). I target half because, they authors suggest that half of the decrease is movements from being on UI benefits to being employed. I match 0.5 weeks decrease for high skill workers and 0.8 weeks decrease for low skill workers.

7.3 Counterfactual Policies

I run several counterfactual scenarios in which the government changes their reemployment service and assessment policies. The results are reported in the next several tables.

For each policy, I examine the percent welfare change measured by consumption, the change in cost, the change in the unemployment rate and the share not receiving unemployment insurance.

7.3.1 Expand Policy to be Required for All Unemployed Workers

In Table 12, I show the results if all individuals are required to participate in the program. I find that this increases costs by 4.9% and has a modest increase on overall welfare for both types. The unemployment rate falls from 5.0% to 4.9% for the low skill worker and to 5.1% from a baseline of 5.2% for the high skill worker. Finally, I find that the share of unemployed not receiving UI increase from 0.6% to 4.6% and 0.4% to 3.4% for low and high skill workers respectively. This is from a mix of drop out and disqualification.

	Low-Type	High-Type
Δ Welfare	0.93%	0.13%
Unemployment Rate	4.85%	5.09%
Δ Unemployment Rate	-0.20 pp	-0.08 pp
Share No UI	4.57%	3.42%
Δ Share No UI	4.00 pp	3.42 pp

Table 12: Counterfactual: All Unemployed Participate in the Program

7.3.2 Expand Policy to be Required for Unemployed Workers and Vary the Disqualification Strictness

To further explore UI access, I run two more counterfactuals. In Table 13, I add full enforcement of disqualification strictness to the above policy of full participation. In Table 14 I allow no enforcement. In the full enforcement case, costs decrease compared to the prior counterfactual because more individuals are no longer receiving UI (only up 0.38% compared to the current policy). Welfare for the low skill workers slightly declines, and there is also a considerable increase in the share of both types of workers not receiving UI. Whether this is a positive or negative depends on how one would characterize the different eligibility rules that could lead to disqualification: are some barriers to access or are they all appropriate for the program? Further research on the types of eligibility issues and reason for the issues will be explored in future research.

In Table 14 I report the values with no eligibility enforcement. Costs are highest in this case, up 6.44% compared to the baseline. In this case, the reason for not receiving UI is from dropping out–not because of eligibility enforcement. If this is due to not needing UI, it could be positive. However, if program attendance is just difficult for certain workers, this indicates this program would increase access issues compared to the baseline, and the access issue is worse for low-type workers. However, workers are still overall better off compared to the baseline.

	Low-Type	High-Type
Δ Welfare	-0.87%	0.25%
Unemployment Rate	4.79%	5.10%
Δ Unemployment Rate	-0.26 pp	-0.08 pp
Share No UI	10.10%	7.28%
Δ Share No UI	9.53 pp	6.91 pp

Table 13: Counterfactual: All Unemployed Participate in the Program and Full Enforcement of Eligibility Issues

	Low-Type	High-Type
Δ Welfare	1.55%	0.08%
Unemployment Rate	4.87%	5.09%
Δ Unemployment Rate	-0.17 pp	-0.08 pp
Share No UI	2.71%	2.10%
Δ Share No UI	2.14 pp	1.73 pp

Table 14: Full Participation and No Eligibility Enforcement

7.3.3 Decrease UI Replacement Rates

Finally, in the last counterfactual I decrease the replacement rate to be 95% of the baseline rate for both types of workers. The results are reported in Table 15 This leads to similar decreases in the unemployment rates compared to the first counterfactual scenario of universal REA program adoption. Costs also decrease by 8.39%. However, it causes a welfare loss for both types of workers.

	Low-Type	High-Type
Δ Welfare	-3.48%	-0.49%
Unemployment Rate	4.84%	4.99%
Δ Unemployment Rate	-0.21 pp	-0.18 pp
Share No UI	0.62%	0.40%
Δ Share No UI	0.05 pp	0.03 pp

Table 15: Counterfactual: Decrease Replacement Rate to 95% of Current Replacement Rate

8 Conclusion

In this paper, I explore reemployment service and eligibility assessment requirements in the context of Unemployment Insurance policy. In the first part of my analysis, I examine whether the implementation of the Reemployment and Eligibility Assessment program within the Unemployment Insurance system had an effect on worker outcomes. Using proxy measures on how states implemented their REA programs, I find that the execution matters for worker outcomes. More rigorous programs lead to increases in earnings and decreases in the duration unemployed. In the second part of my analysis, I develop a job search model incorporating features of these programs. I find that increasing participation requirements and/or eligibility enforcement lead to increases in costs, decreases in the unemployment rate, and increases in overall welfare at the expense of decreasing access to UI. I find that decreasing UI replacement rates can lead to similar decreases in unemployment rates but it decreases overall welfare. Overall, reemployment service and assessment programs can be effective in UI policy but the implementation of these programs is critical in ensuring the intended impact.

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9 Appendix

Table 1: REA Participation and Disqualification Measures as a Fraction of First Payments, Include States without the Program

	p25	p50	mean	p75	SD
% First scheduled meetings	0.00	4.25	9.51	14.04	13.55
% Completed meetings	0.00	3.21	9.12	11.96	13.81
% Disqualified due to not reporting	0.00	0.02	0.98	0.88	2.30
% Reemployment services or training	0.00	1.97	6.79	8.96	10.90
% REA meeting resulted in disqualification or overpayment	0.00	0.02	0.63	0.36	2.13

Quarterly data is from DOL ETA reports. Data is from 2005-2015. Statistics are for all states, including states without the program.

Table 2: Composition of Unemployed and REA Treatment

VARIABLES	(1) % Scheduled	(2) %Comp.	(3) %Disq No Rep	(4) %Training	(5) %Disq.or Overpay
College Plus	-0.0315	-0.133	-0.0239	-0.0292	0.121*
	(0.282)	(0.293)	(0.0715)	(0.245)	(0.0630)
Agricult., Forest, Fish	0.612	1.626	0.714	2.399	0.369
	(2.004)	(2.078)	(0.508)	(1.738)	(0.448)
Mining	-1.018	0.815	0.0785	0.583	0.652
	(2.488)	(2.580)	(0.631)	(2.158)	(0.556)
Construct.	-0.429	0.225	0.490	1.321	0.341
	(1.854)	(1.923)	(0.470)	(1.608)	(0.414)
Manufact.	0.199	0.339	0.562	1.681	0.478
	(1.942)	(2.013)	(0.492)	(1.684)	(0.434)
Public Utilities	0.332	0.909	0.379	2.239	0.492
	(1.966)	(2.038)	(0.498)	(1.705)	(0.439)
Wholesale Trade	0.560	0.145	0.720	2.174	0.559
	(2.097)	(2.174)	(0.531)	(1.819)	(0.469)
Retail Trade	-0.634	-0.325	0.313	1.450	0.465
	(1.946)	(2.018)	(0.493)	(1.688)	(0.435)
Fin., Insur., Real Est.	-0.183	-0.101	0.717	1.292	0.480
	(1.985)	(2.058)	(0.503)	(1.721)	(0.444)
Bus./Repair Serv.	0.739	1.020	0.668	2.422	0.538
	(1.898)	(1.969)	(0.481)	(1.647)	(0.424)
Personal Serv.	0.446	0.579	0.467	1.719	0.507
	(1.985)	(2.059)	(0.503)	(1.722)	(0.444)
Entertain./Rec. Serv.	0.508	1.058	0.682	2.226	0.320
	(1.949)	(2.022)	(0.494)	(1.691)	(0.436)
Prof. Serv.	0.435	1.414	0.640	2.309	0.584
	(1.931)	(2.002)	(0.489)	(1.674)	(0.431)
Public Admin.	1.258	2.255	0.620	2.892*	0.516
	(1.969)	(2.041)	(0.499)	(1.707)	(0.440)
Mgmt., Bus., Sci., Arts	-0.276	-0.107	-0.301	-1.719	-0.541
	(1.995)	(2.068)	(0.505)	(1.730)	(0.446)
Bus. Ops. Spec.	0.734	1.476	-0.784	-0.0568	-0.835*
	(1.986)	(2.060)	(0.503)	(1.723)	(0.444)
Financial Spec.	0.0668	0.422	-0.132	-1.545	-0.850*
	(2.273)	(2.357)	(0.576)	(1.971)	(0.508)
Computer & Math	-0.705	-0.764	-0.765	-2.131	-0.668
	(2.151)	(2.230)	(0.545)	(1.866)	(0.481)
Architecture & Engineer.	-0.828	-0.403	-1.244**	-1.689	-1.070**
	(2.374)	(2.462)	(0.602)	(2.059)	(0.531)
Technicians	2.953	-0.917	-0.281	-1.270	-0.731
	(2.854)	(2.960)	(0.723)	(2.476)	(0.638)
Life, Phys., and Soc. Sci.	1.689	-0.898	-0.579	-0.0377	-0.728
	(2.630)	(2.728)	(0.667)	(2.282)	(0.588)
Community & Soc. Serv.	-2.583	-3.463	-0.630	-4.036*	-1.069**
	(2.371)	(2.459)	(0.601)	(2.056)	(0.530)
Legal	-1.635	-3.448	-1.452**	-2.613	-0.700
	(2.629)	(2.726)	(0.666)	(2.280)	(0.588)
Educ., Train., Library	0.888	-0.250	-0.344	-1.455	-0.501
	(1.997)	(2.071)	(0.506)	(1.732)	(0.446)
Arts, Design, Entertain., Sports	-1.262	-0.544	-0.598	-1.857	-0.408
	(2.120)	(2.198)	(0.537)	(1.839)	(0.474)
Healthcare Practitioner & Tech.	-0.505	-0.862	-0.703	-2.674	-0.670
	(2.215)	(2.296)	(0.561)	(1.921)	(0.495)
Healthcare Support	-2.215	-3.386	-0.920*	-3.707**	-0.523
	(2.009)	(2.083)	(0.509)	(1.743)	(0.449)
Protective Serv.	-0.670	-1.369	-0.979*	-1.585	-0.406
	(1.971)	(2.044)	(0.499)	(1.709)	(0.440)
Food Prep & Serving	0.0411	0.0422	-0.473	-1.568	-0.701
	(2.013)	(2.087)	(0.510)	(1.746)	(0.450)
Bldg. Cleaning and Maintenance	-1.979	-2.001	-0.569	-3.095*	-0.621
	(1.951)	(2.023)	(0.494)	(1.692)	(0.436)
Personal Care & Serv.	-1.184	-1.511	-0.684	-2.022	-0.761*
	(1.953)	(2.025)	(0.495)	(1.694)	(0.437)
Sales	0.235	0.0143	-0.453	-1.620	-0.591
	(1.977)	(2.050)	(0.501)	(1.715)	(0.442)
Office & Admin. Support	-0.627	-0.696	-0.630	-2.291	-0.657
	(1.968)	(2.041)	(0.499)	(1.707)	(0.440)
Farm, Fish, Forestry	-0.395	-1.502	-0.860	-1.946	-0.696
	(2.153)	(2.232)	(0.545)	(1.867)	(0.481)
Construction	0.499	-0.0514	-0.386	-1.097	-0.438
	(1.864)	(1.933)	(0.472)	(1.617)	(0.417)
Extraction	0.680	-1.313	0.508	-1.797	-1.124
	(3.189)	(3.307)	(0.808)	(2.766)	(0.713)
Install, Maintain, Repair	-0.00498	0.263	-0.652	-2.006	-0.678
	(1.992)	(2.066)	(0.505)	(1.728)	(0.445)
Prod.	-0.598	-0.677	-0.541	-1.716	-0.619
	(1.980)	(2.053)	(0.502)	(1.717)	(0.442)
Transport. & Material Moving	0.311	0.407	-0.373	-1.364	-0.437
	(1.925)	(1.996)	(0.488)	(1.669)	(0.430)
Unemployment Rate	-2.258***	-2.021***	-0.192	-1.998***	-0.254
	(0.718)	(0.745)	(0.182)	(0.623)	(0.161)
Observations	520	520	520	520	520
R-squared	0.666	0.669	0.622	0.614	0.439

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This reports results for regressions with the alternate implementation measures as the dependent variables. The state-level independent variables are the share of the unemployed who have a bachelor's or higher, the shares of the unemployed made up of individuals from different industries, the shares of the unemployed from different occupations, and the unemployment rate. There are state and time fixed effects. This table reports results for states/years with the REA program.

Table 3: Composition of Unemployed and REA Treatment

VARIABLES	(1) % Scheduled	(2) %Comp.	(3) %Disq No Rep	(4) %Training	(5) %Disq.or Overpay
College Plus	-0.0924	-0.0554	-0.0694*	0.00669	0.0755**
	(0.172)	(0.183)	(0.0409)	(0.142)	(0.0319)
Agricult., Forest, Fish	0.979	0.954	0.502	2.009*	0.0159
	(1.426)	(1.513)	(0.338)	(1.178)	(0.264)
Mining	0.0207	-0.0277	0.254	1.079	0.0874
	(1.538)	(1.631)	(0.365)	(1.271)	(0.285)
Construct.	0.366	0.00602	0.455	1.519	0.0493
	(1.362)	(1.444)	(0.323)	(1.125)	(0.252)
Manufact.	0.681	0.267	0.527	1.667	0.0507
	(1.385)	(1.469)	(0.329)	(1.144)	(0.256)
Public Utilities	0.608	0.482	0.384	1.822	0.0900
	(1.398)	(1.483)	(0.332)	(1.155)	(0.259)
Wholesale Trade	0.976	0.734	0.466	1.968	0.134
	(1.450)	(1.538)	(0.344)	(1.198)	(0.269)
Retail Trade	0.318	-0.0620	0.294	1.577	0.0488
	(1.386)	(1.470)	(0.329)	(1.145)	(0.257)
Fin., Insur., Real Est.	0.710	0.112	0.352	1.577	0.0659
	(1.408)	(1.493)	(0.334)	(1.163)	(0.261)
Bus./Repair Serv.	0.644	0.277	0.455	1.790	0.0881
	(1.377)	(1.460)	(0.327)	(1.137)	(0.255)
Personal Serv.	0.733	0.299	0.352	1.614	0.101
	(1.402)	(1.487)	(0.333)	(1.158)	(0.260)
Entertain./Rec. Serv.	0.853	0.393	0.461	2.053*	0.0271
	(1.392)	(1.477)	(0.330)	(1.150)	(0.258)
Prof. Serv.	0.823	0.723	0.428	2.053*	0.112
	(1.377)	(1.461)	(0.327)	(1.138)	(0.255)
Public Admin.	1.225	1.060	0.553*	2.257*	0.118
	(1.410)	(1.495)	(0.335)	(1.165)	(0.261)
Mgmt., Bus., Sci., Arts	-0.886	-0.398	-0.407	-1.881	-0.124
	(1.415)	(1.500)	(0.336)	(1.169)	(0.262)
Bus. Ops. Spec.	-0.450	0.237	-0.437	-0.852	-0.319
	(1.433)	(1.520)	(0.340)	(1.184)	(0.265)
Financial Spec.	-0.228	-0.0492	-0.193	-1.493	-0.284
	(1.523)	(1.615)	(0.361)	(1.258)	(0.282)
Computer & Math	-1.143	-1.235	-0.487	-2.396**	-0.176
	(1.476)	(1.565)	(0.350)	(1.220)	(0.273)
Architecture & Engineer.	-1.418	-1.260	-0.641*	-2.146*	-0.431
	(1.559)	(1.653)	(0.370)	(1.288)	(0.289)
Technicians	1.139	-0.297	-0.189	-1.369	-0.275
	(1.851)	(1.963)	(0.439)	(1.529)	(0.343)
Life, Phys., and Soc. Sci.	-0.271	-0.584	-0.212	-1.266	-0.230
	(1.675)	(1.776)	(0.397)	(1.384)	(0.310)
Community & Soc. Serv.	-1.375	-1.215	-0.587	-2.405*	-0.185
	(1.556)	(1.650)	(0.369)	(1.286)	(0.288)
Legal	-3.087*	-2.495	-0.922**	-3.118**	-0.243
	(1.719)	(1.823)	(0.408)	(1.420)	(0.318)
Educ., Train., Library	-0.528	-0.626	-0.384	-1.936	-0.129
	(1.427)	(1.513)	(0.339)	(1.179)	(0.264)
Arts, Design, Entertain., Sports	-1.101	-0.397	-0.537	-1.853	-0.105
	(1.459)	(1.548)	(0.346)	(1.206)	(0.270)
Healthcare Practitioner & Tech.	-1.098	-0.861	-0.532	-2.459*	-0.141
	(1.528)	(1.620)	(0.363)	(1.262)	(0.283)
Healthcare Support	-1.970	-2.282	-0.576*	-3.043***	-0.106
	(1.422)	(1.508)	(0.337)	(1.174)	(0.263)
Protective Serv.	-0.216	0.0208	-0.442	-1.120	-0.0179
	(1.387)	(1.471)	(0.329)	(1.146)	(0.257)
Food Prep & Serving	-0.565	-0.118	-0.367	-1.552	-0.184
	(1.410)	(1.496)	(0.335)	(1.165)	(0.261)
Bldg. Cleaning and Maintenance	-1.595	-1.094	-0.501	-2.263*	-0.125
	(1.399)	(1.484)	(0.332)	(1.156)	(0.259)
Personal Care & Serv.	-1.138	-0.628	-0.420	-1.738	-0.198
	(1.399)	(1.483)	(0.332)	(1.155)	(0.259)
Sales	-0.466	-0.191	-0.359	-1.589	-0.116
	(1.396)	(1.481)	(0.331)	(1.154)	(0.259)
Office & Admin. Support	-1.307	-0.872	-0.475	-2.206*	-0.189
	(1.389)	(1.473)	(0.329)	(1.147)	(0.257)
Farm, Fish, Forestry	-0.875	-0.668	-0.564	-1.650	-0.158
	(1.468)	(1.557)	(0.348)	(1.213)	(0.272)
Construction	-0.355	0.109	-0.402	-1.395	-0.127
	(1.363)	(1.445)	(0.323)	(1.126)	(0.252)
Extraction	-0.551	-0.451	-0.418	-1.423	-0.314
	(1.728)	(1.832)	(0.410)	(1.427)	(0.320)
Install, Maintain, Repair	-0.318	0.438	-0.450	-1.378	-0.153
	(1.401)	(1.486)	(0.332)	(1.158)	(0.259)
Prod.	-0.950	-0.716	-0.531	-1.889	-0.146
	(1.393)	(1.477)	(0.331)	(1.151)	(0.258)
Transport. & Material Moving	-0.824	-0.400	-0.396	-1.690	-0.120
	(1.382)	(1.465)	(0.328)	(1.142)	(0.256)
Unemployment Rate	-1.478***	-1.695***	-0.230**	-1.388***	-0.121
	(0.420)	(0.445)	(0.0997)	(0.347)	(0.0778)
Observations	1,020	1,020	1,020	1,020	1,020
R-squared	0.635	0.588	0.460	0.565	0.312

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This reports results for regressions with the alternate implementation measures as the dependent variables (no program is zero). The state-level independent variables are the share of the unemployed who have a bachelor's or higher, the shares of the unemployed made up of individuals from different industries, the shares of the unemployed from different occupations, and the unemployment rate. There are state and time fixed effects.