Unemployment Insurance and The Scarring Effects of Unemployment on Employment Quality

(Additional Details)

2023 PSID Annual User Conference

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Background

Unemployment

- Negatively affects likelihood of future employment, EQ characteristics (wages, permanency, benefits), and job match (by education, prior experience)
- More prominently affects lower-paid, younger and older, and female workers. Less clear/under-studied differences by race and ethnicity
- No research assessing multi-dimensional EQ, or moderation by prior EQ

Unemployment Insurance (UI)

- Likely mitigates these harms, but evidence is mostly EU-based and mixed:
    1. Across populations and contexts (e.g. by country, or in vs. not in recession)
    2. Depending on the UI feature assessed (UI receipt, max. duration, benefit amount)
- More prominently benefits those with low initial wages & wealth and less education, as well as those younger, women, and non-white

Study Aims

1. **Estimate the ATT of recent unemployment on subsequent EQ**
   - ATT (vs. ATE) as exchangeability of treated and untreated individuals unlikely
2. **Examine whether UI features modify this effect**
   - By UI receipt, maximum weeks receivable, maximum benefit amount
3. **Examine modification of Aims 1 and 2**
   - By gender, race and ethnicity, and baseline EQ

Exposure, Moderator, Outcome

Exposure (A)

Unemployment during the 12 months post-interview in *T*

Outcome (Y)

Z-Score Multi-Dimensional EQ Score 2+ years post-interview

UI Moderators (M)

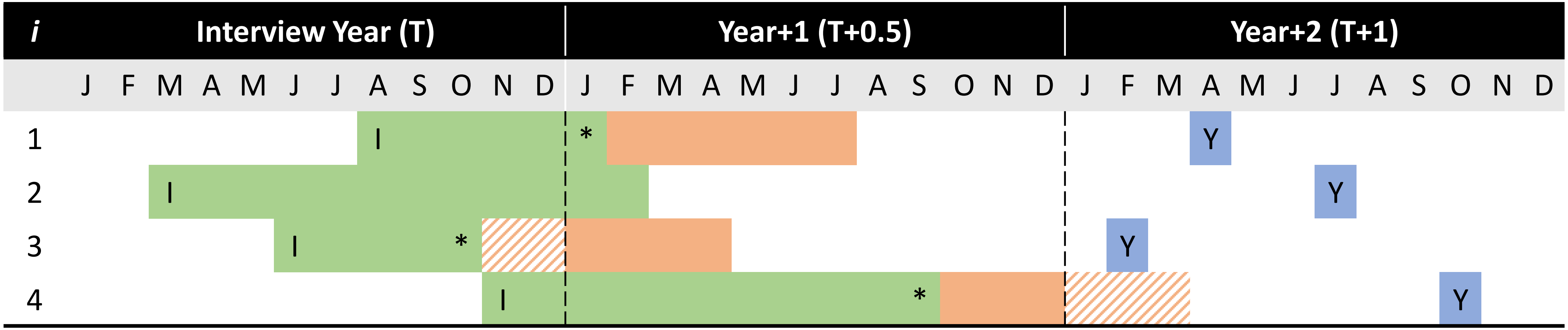
1. UI receipt within 6 months of unemployment
2. Maximum weeks of UI receivable (< 2001-2017 State Median: No, Yes)
3. Maximum receivable UI amount (< 2001-2017 State Median: No, Yes)
4. ~~Monthly UI amount received~~ (unreliable reported amounts)

PSID Data Prep Needed for A, Y, M

PSID collects monthly data in retrospect on:

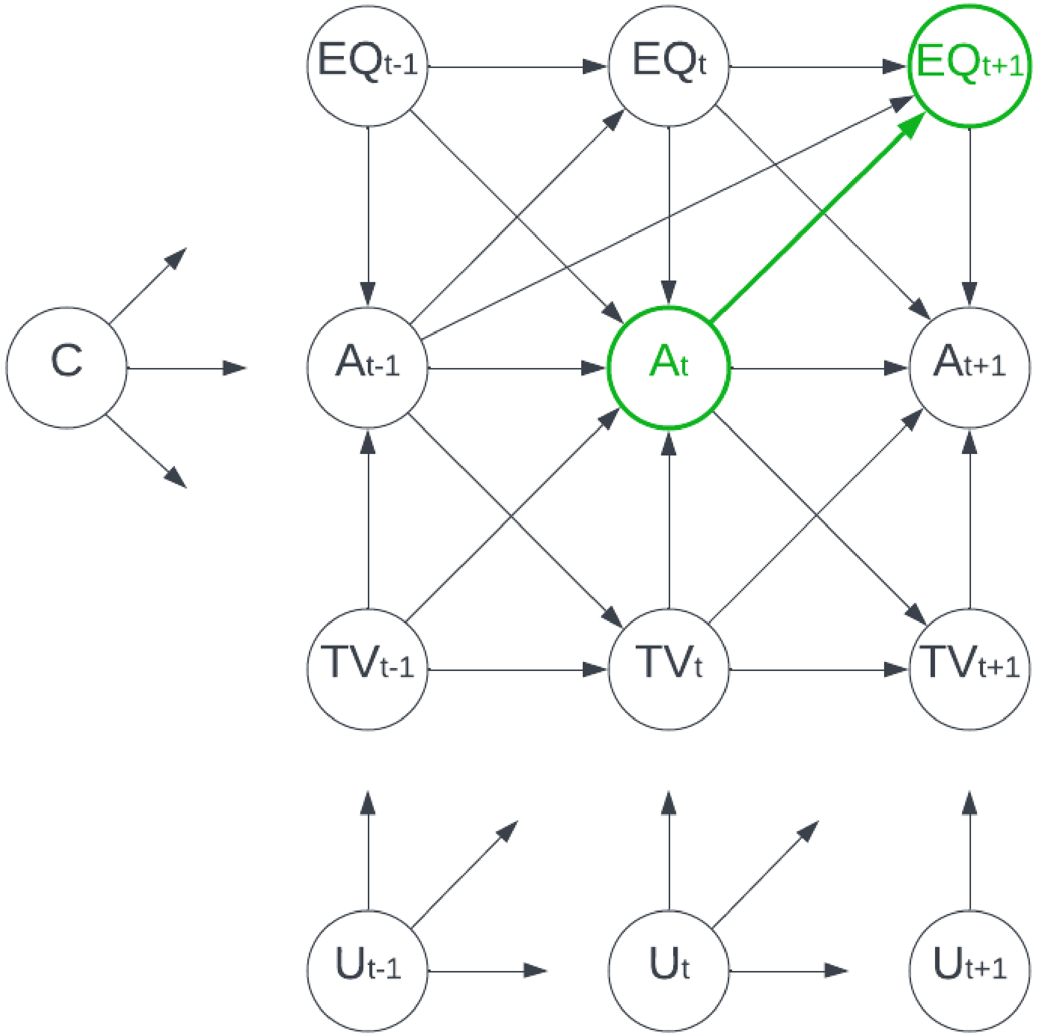
- Employment status (for 24 months covering T & T+0.5 in year T+1)
- UI recipiency and amount (for 12 months covering T+0.5 in year T+1)

I’d plan on using this information to determine A and M as illustrated below:



I: Interview month at *T*. Green: Unemployment within 12-months post-I. *: First Unemployment. Orange: UI receipt within 6 months post-unemployment. Dashed Orange: Months in which UI recipiency information was not collected.
Y: EQ at subsequent interview *T+1*.

Assumed Unemployment → EQ Relationship



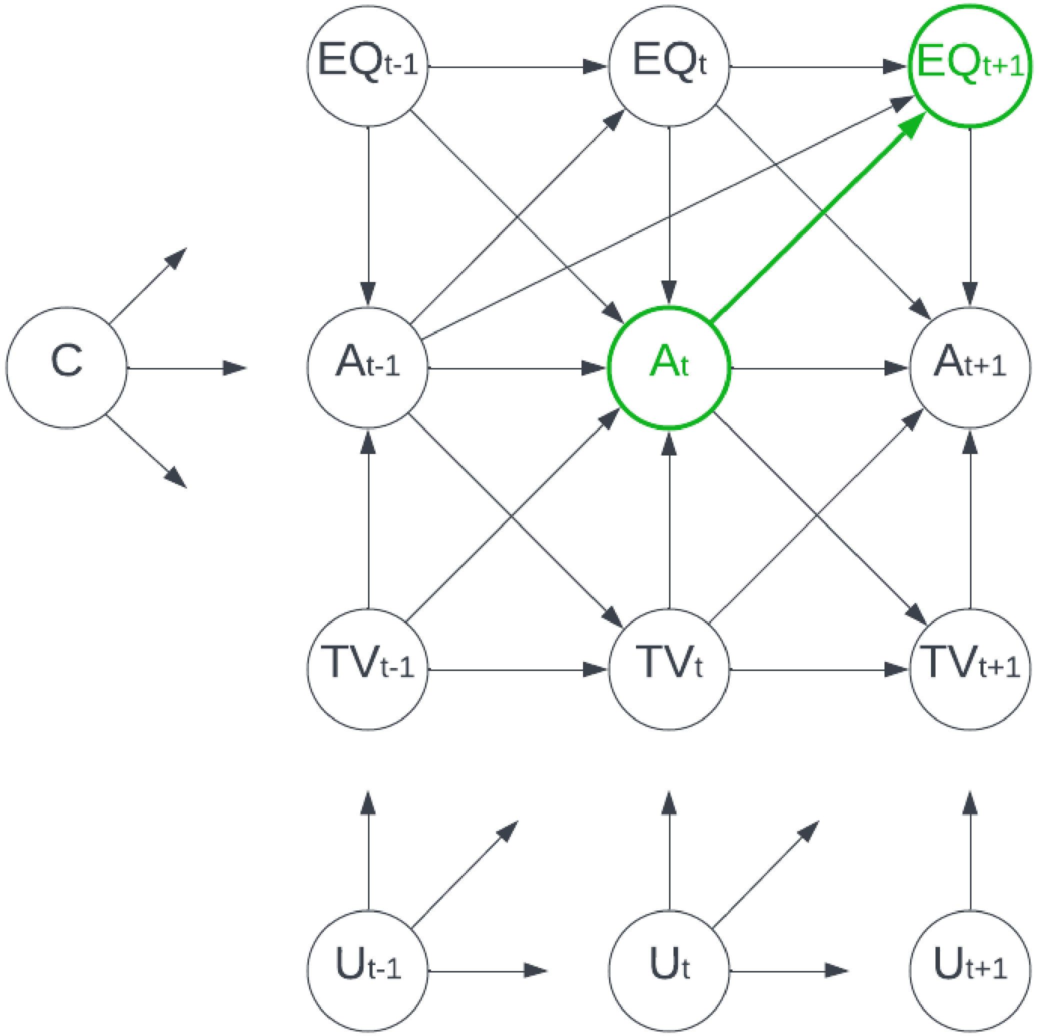
DAG Legend

t	Time index (none = fixed)
C	Baseline covariates
A	Unemployment Status (**exposure**)
EQ	Current/most recent job EQ (**outcome**)
TV	Measured time-varying covariates
U	Unmeasured time-varying covariates

Notes

- C is assumed to affect everything, and includes measured and unmeasured factors
- U_t is assumed to affect everything at *t*, *t*+1
- UI at *t* is expected to modify ATT(A_t → EQ_{t+1})

Assumed Unemployment → EQ Relationship



<u>Assumed/Implied Causal Features</u>

- Unmeasured unit- and time-FE
- Time-varying confounding
- Exposure-outcome feedback
- Multiple time-points *t*
- Exposure possible at any *t*
- Exposure-switching over time
- Lagged exposure effects
- Markov-1 assumption (M-2 for A)

How can we estimate this ATT?

Methods Used In Existing Research

Most studies around scarring effects and UI moderation have used:

- Differences-in-differences (DiD) approaches
- Individual and two-way fixed effects approaches
- Regression discontinuity
- Structural Equation Modelling (SEMs)
- Propensity Score matching techniques

These often exploit natural experiments where: 1) a single threshold defines exposure status (e.g. time, age), or 2) individuals transition from unexposed to exposed once.

In our assumed causal scenario, each methods would be violated in 1+ way.

How can we estimate this ATT?

Implemented Approach

Imai, Kim & Wang (2021) propose a semi-parametric two-way fixed effect estimator which allows for each of the causal features in our study (below right)

The standard TWFE estimator can't work in our scenario unless we assume across units either:

1. The within-unit causal effect is constant, or
2. The frequency of 'exposure' is constant

Both of which seem unreasonable where we expect social modification of effects.

Assumed/Implied Causal Features

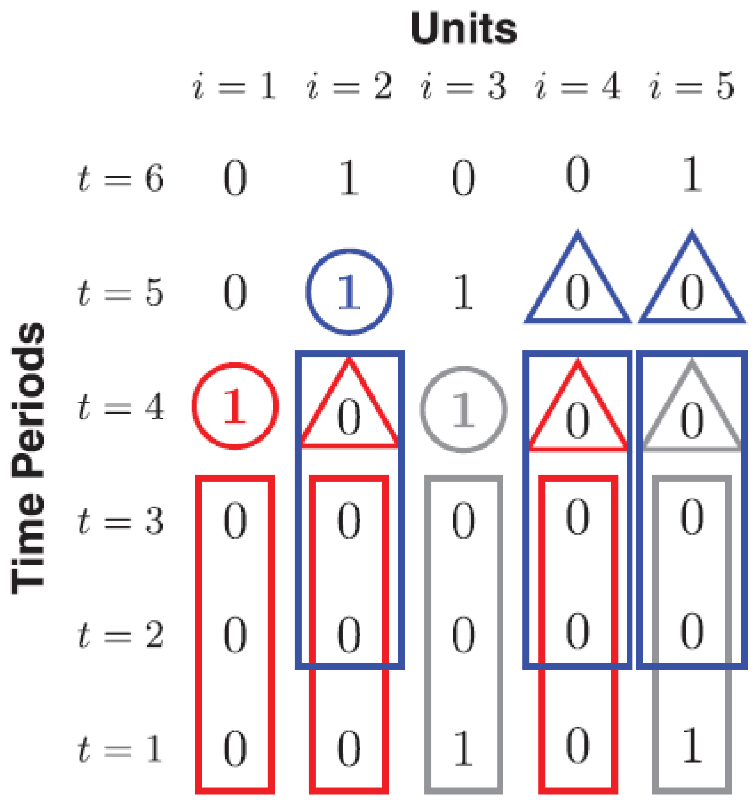
- Unmeasured unit- and time-FE
- Time-varying confounding
- Exposure-outcome feedback
- Multiple time-points *t*
- Exposure possible at any *t*
- Exposure-switching over time
- Lagged exposure effects
- Markov-1 assumption (M-2 for A,EQ)

How can we estimate this ATT?

<u>**Implemented Approach**</u>

The proposed two-way fixed effect estimator works as follows:

1. Create a *matched set* M_{it} for each newly exposed observation (i,*t*) with all unexposed observations (i’,*t*) with the same exposure history up to some lag *L* (e.g. 3 time-points)

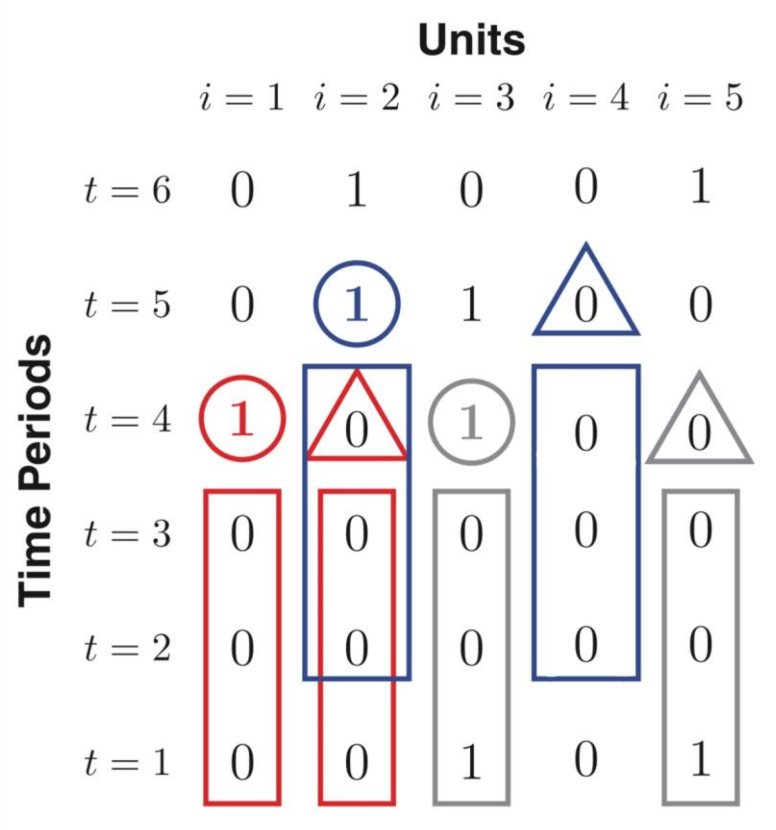


How can we estimate this ATT?

Implemented Approach

The proposed two-way fixed effect estimator works as follows:

2. Create a *refined* matched set R_{it} from M_{it} for each newly exposed observation, restricting to the set of unexposed observations with the most similar covariate histories based on, e.g.:
   - Mahalanobis distance
   - Propensity scores **(Implemented)**
   - Inverse Probability Weights



How can we estimate this ATT?

Implemented Approach

The proposed two-way fixed effect estimator works as follows:

3. Employ a DiD estimator (bottom) to estimate our causal effect of interest, weighting each matched set-specific ATT_{it} estimate via D_{it} based on how often that exposed unit *i* contributes to the analysis.
   - The DiD estimator compares:
     1. Pre-post outcome difference in the newly exposed observation
     2. Weighted average pre-post outcome differences across matched unexposed observations
   - This DiD estimator is equivalent to a weighted linear two-way fixed effect estimator, weighting each observation in a way that accounts for matching

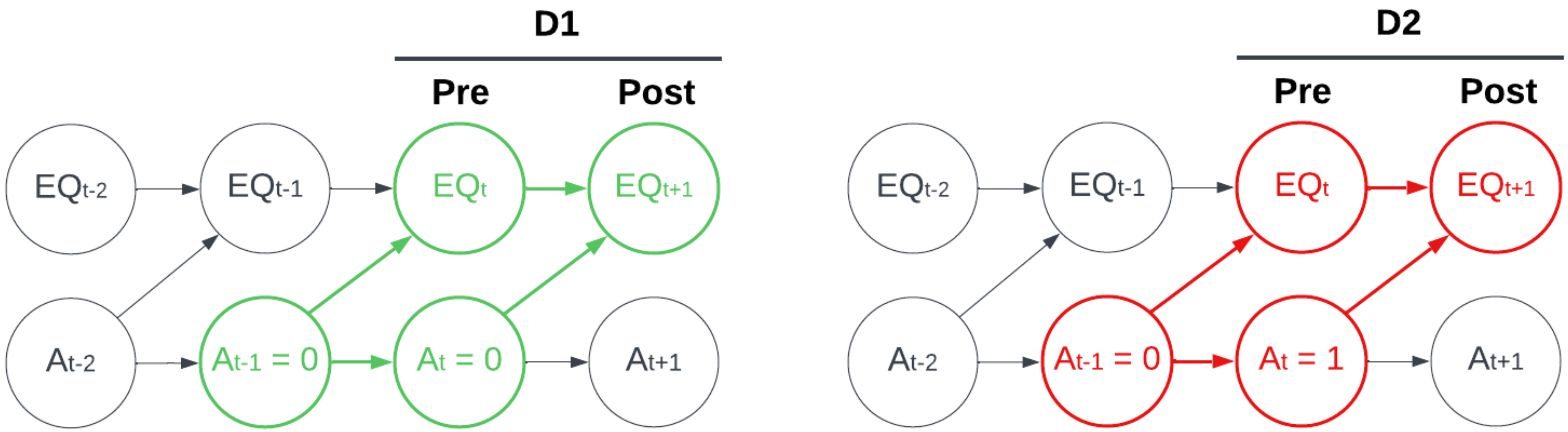
$$\hat{\delta}(F, L) = \frac{1}{\sum_{i=1}^{N} \sum_{t=L+1}^{T-F} D_{it}} \sum_{i=1}^{N} \sum_{t=L+1}^{T-F} D_{it} \left\{ \left(Y_{i,t+F} - Y_{i,t-1}\right) - \sum_{i' \in \mathcal{M}_{it}} w_{it}^{i'} \left(Y_{i',t+F} - Y_{i',t-1}\right) \right\}$$

Accounting for Structural Outcome Missingness

We want to estimate ATT($A_t \rightarrow EQ_{t+1}$) using a DiD-based approach with:

- **D1:** Outcomes at *t* and *t+1* among those remaining employed ($A_{t-1} = 0$, $A_t = 0$), vs.
- **D2:** Outcomes at *t* and *t+1* among those becoming unemployed ($A_{t-1} = 0$, $A_t = 1$)

We assume A at *t-1* affects EQ at *t*, so ideally compare EQ at *t* and *t+1.*



Accounting for Structural Outcome Missingness

Respondents unemployed at *t* have no EQ though (since they're unemployed), so we cannot use this EQ measure as 'post-exposure EQ' for (i,*t-1*) or 'baseline EQ' for (i,*t+1*).

We always want:

1) Baseline EQ to always precede post-exposure EQ
2) Post-exposure EQ to be from a *subsequent* wave to *t* if (i,*t*) is used as a 'post' observation in a DiD comparison

To accommodate this, we assign 'pre' and 'post' EQ for each participant at each time *t* from neighbouring interviews under each of the below conditions:

A_{t-1} , A_t , A_{t+1}	***t* used as 'post' in DiD?**	**'Pre' EQ (*t*)**	**'Post' EQ (*t*+1)**
0, 0, 0	Yes	Most recent ≤ *t*	Nearest subsequent > *t*
0, 1, A	Yes	Most recent ≤ *t*	Nearest subsequent > *t*
0, 0, 1	Sometimes	Second most recent ≤ *t*	Most recent ≤ *t*
1, A, A	No	Second most recent ≤ *t*	Most recent ≤ *t*

Explanations and Planned Sanity Checks for Counter-Intuitive Findings

1. **Selection on reported EQ (if employed) & covariates skewing sample?**
   - Repeat analyses after multiple imputation
2. **Different lags and leads for pre- and post-exposure EQ?**
   - Restrict to those with EQ ≤ 4 years from pre- and post-observations, which may itself be a lesser issue post-imputation
3. **Unaccounted-for time-varying confounding?**
   - Explore other covariates (e.g. past-quarter state unemployment, GPD/capita)
4. **Different lengths of unemployment pre-re-employment?**
   - Calculate (where possible) and stratify by
5. **Possible source-specific issue related to retrospective exposure and moderator ascertainment and biennial outcome measurement?**
   - Explore replication of study in different data source **(Not Going to Do)**

Accounting for Random Covariate Missingness

31% of observations were incomplete across analytic variables.

We accounted for this using multiple imputation, where we:

- Create 35 multiply imputed datasets following guidance from White *et al.* (2011), who recommend creating at least as many imputed datasets as the percentage of incomplete cases.
- Conduct MI within employment strata before re-merging strata post-imputation to best-follow guidance from Sullivan *et al.* (2018), who recommend conducting MI within exposure strata.
  - Some variables (e.g. UI receipt) are structurally implausible for those consistently employed, so we do not impute these variables in MI models for those ‘unexposed’.
- Cluster imputations by individual when imputing our exposure and outcome.

Study Eligibility Restrictions

We restrict the available sample of observations as below:

1. Between 2003 and 2017
2. Aged 18-64 years old
3. Attached to the labor market (employed/temp. laid-off, or unemployed)
4. Not self-employed
5. With known race, ethnicity, gender, nativity, and childhood SES
6. With three consecutive waves in which exposure and outcome status are known
7. With respondents living in the same state over those 3 consecutive waves

Analytic Sample Development Example

We develop our analytic sample in the following steps:

1. Identify the maximum sample per participant where participants are in-theory eligible (e.g. by year, age, labor market attachment).

		Unemployment Status (A) in Wave (T)							
		1	2	3	4	5	6	7	8
Individual	A	1	0	0	1	1	0	1	0
	B	-	0	0	-	0	1	0	-
	C			1	0	0	1	1	1
	D				0	1	-	0	

Grey Shading: Unknown EQ in wave *t*, either due to having unknown unemployment status, missing EQ while employed (A=0), or being unemployed (A=1). Black Shading: Not interviewed.

Analytic Sample Development Example

We develop our analytic sample in the following steps:

2. Use multiple imputation N times (one shown) to impute unemployment status and EQ variables (among others) where missing.

		Unemployment Status (A) in Wave (T)							
		1	2	3	4	5	6	7	8
Individual	A	1	0	0	1	1	0	1	0
	B	1	0	0	1	0	1	0	0
	C			1	0	0	1	1	1
	D				0	1	0	0	

Grey Shading: Unknown EQ in wave *t* due to being unemployed (A=1). Black Shading: Not interviewed.

Analytic Sample Development Example

We develop our analytic sample in the following steps:

3. Identify observations 'newly unemployed' (red) and 'consistently employed' (blue) based on A_{t-1} and A_t.

		Unemployment Status (A) in Wave (T)							
		1	2	3	4	5	6	7	8
Individual	A	1	0	0	1	1	0	1	0
	B	1	0	0	1	0	1	0	0
	C			1	0	0	1	1	1
	D				0	1	0	0	

Grey Shading: Unknown EQ in wave t due to being unemployed (A=1). Black Shading: Not interviewed. Red Shading: Newly Unemployed Observation (i,t) with $A_{t-1} = 0$ and $A_t = 1$. Blue Shading: Consistently Employed Observation (i,t) with $A_{t-1} = 0$ and $A_t = 0$.

Analytic Sample Development Example

We develop our analytic sample in the following steps:

4. Determine ‘pre’ (baseline) and ‘post’ (subsequent) EQ for all wave observations (only highlighting ATT analysis observations here) following the structural outcome missingness solution discussed previously.

	Unemployment Status (A) in Wave (T)							
Individual	1	2	3	4	5	6	7	8
A			(t_2, t_3)	(t_3, t_6)			(t_6, t_8)	
B			(t_2, t_3)	(t_3, t_5)		(t_5, t_7)		~~(t_7, NA)~~
C					(t_4, t_5)	~~(t_5, NA)~~		
D					(t_4, t_6)		~~(t_6, NA)~~	

Grey Shading: Unknown EQ in wave *t* due to being unemployed (A=1). Black Shading: Not interviewed. Red Outline: Newly Unemployed Observation (i,*t*) with $A_{t-1} = 0$ and $A_t = 1$. Strikethrough: Excluded due to missing ‘baseline’ or ‘subsequent’ EQ. Note: Parentheses show waves ‘baseline’ and ‘subsequent’ EQ are taken from.

Study Characteristics

Data: 1984-2019 PSID Data (Analysis Years: 2003-2017)

Analysis N: 8752 individuals, 45,193 observations (Mean Follow-Up: 6.6 Years)

Characteristic		**Sample**			
		Complete Case		MI Dataset Averages	
		Consistently Employed	Recently Unemployed	Consistently Employed	Recently Unemployed
	N Individuals (Observations)	6677 (22,963)	3080 (3537)	6934 (24,226)	3431 (3969)
Age	Mean (SD)	43.2 (10.0)	38.4 (10.1)	43.2 (10.0)	38.4 (10.2)
Gender (%)*	Male	3151 (47)	1478 (48)	3276 (47)	1626 (47)
Race and Ethnicity (%)*	NH White	3984 (54)	1781 (53)	4098 (54)	1942 (51)
	NH Black	1982 (30)	981 (32)	2092 (30)	1122 (33)
	NH Other	534 (8)	231 (8)	555 (8)	261 (8)
	Hispanic	544 (8)	246 (8)	575 (8)	287 (8)
Baseline EQ	Mean (SD), NA	0.14 (0.37), 241	-0.03 (0.42), 70	0.13 (0.40), 51	-0.06 (0.46), 29
Pre-Post EQ Change	Mean (SD), NA	0.34 (0.48), 241	-0.39 (0.86), 70	0.32 (0.54), 51	-0.33 (0.88), 29
UI Receipt (%), NA	Yes	-	353 (13), 810	-	508 (13), 0

* Counts and percentages reflect characteristics of unique individuals, excluding repeated measurements.

Study Characteristics

Matching by year and state over {*t-2,t-1,t*} and employment over {*t-2, t-1*}, there were:

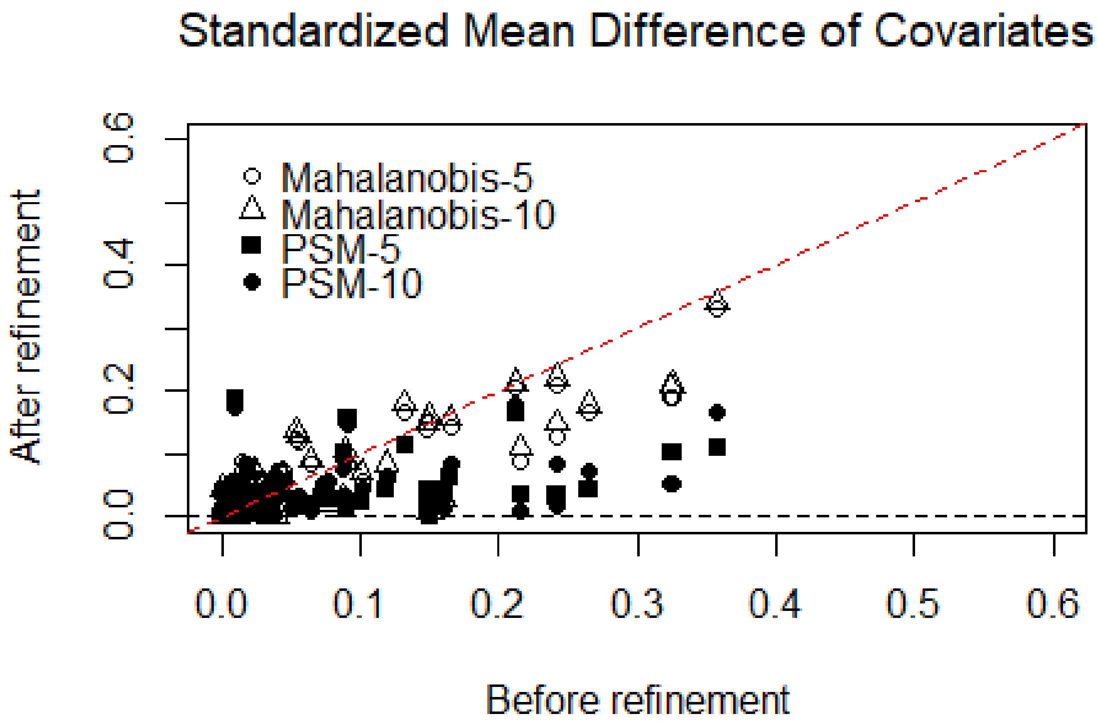
Pooled Average Characteristics Across Multiply Imputed Dataset Analyses

Observation Group	All	UI Receipt					
		No	Yes	< Med. Max Dur.	≥ Med. Max Dur.	< Med. Max Ben.	≥ Med. Max Ben.
Matched Exposed (N)	2581	2236	346	8	338	139	212
Unmatched Exposed (N)	657	-	-	-	-	-	-
Matched Unexposed Per Exposed (Median N [IQR])	40 [7, 104]	74 [20, 112]	86 [28, 116]	84 [49, 93]	86 [28, 116]	77 [21, 101]	90 [37, 129]

PS matching approaches also consider covariate history. Set sizes shown are pre-refinement, with all sets restricted to the 10 most-similar unexposed units per exposed unit after refinement. Maximum UI duration and benefit amount are state-level factors, not reflective of the duration and benefit received. 2001-2017 Median State Maximum UI Duration: 26 weeks. 2001-2017 Median State Maximum UI Benefit for those with dependents: $390/week.

Matched Set Covariate Balance

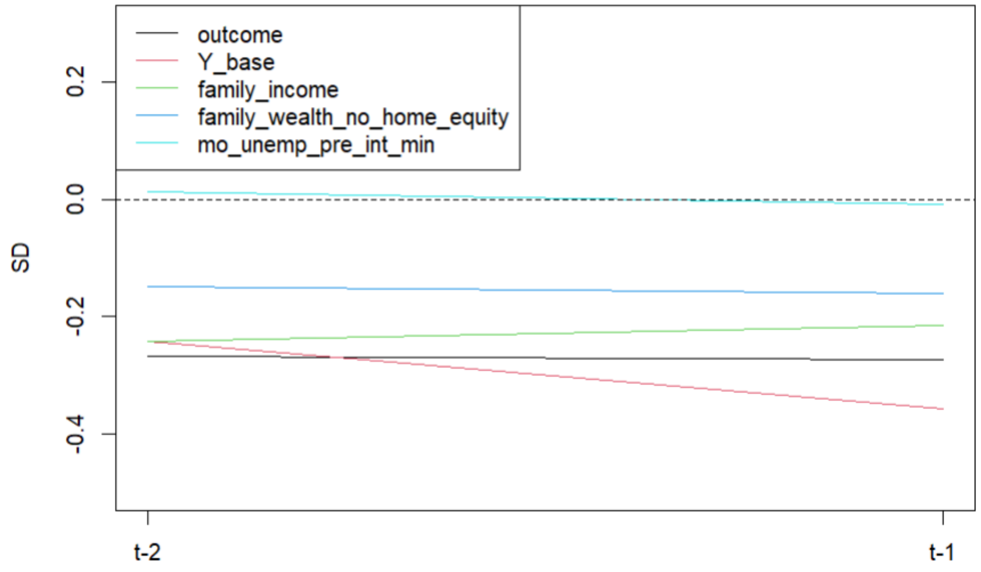
We determined which refinement approach to use and the and number of unexposed observations per exposed observation to include in refined sets by examining which combination provided the best within-set covariate balance between exposed and exposed observations. From this, chose propensity score matching (PSM) with up to 10 unexposed observations per ‘newly exposed’ observation.



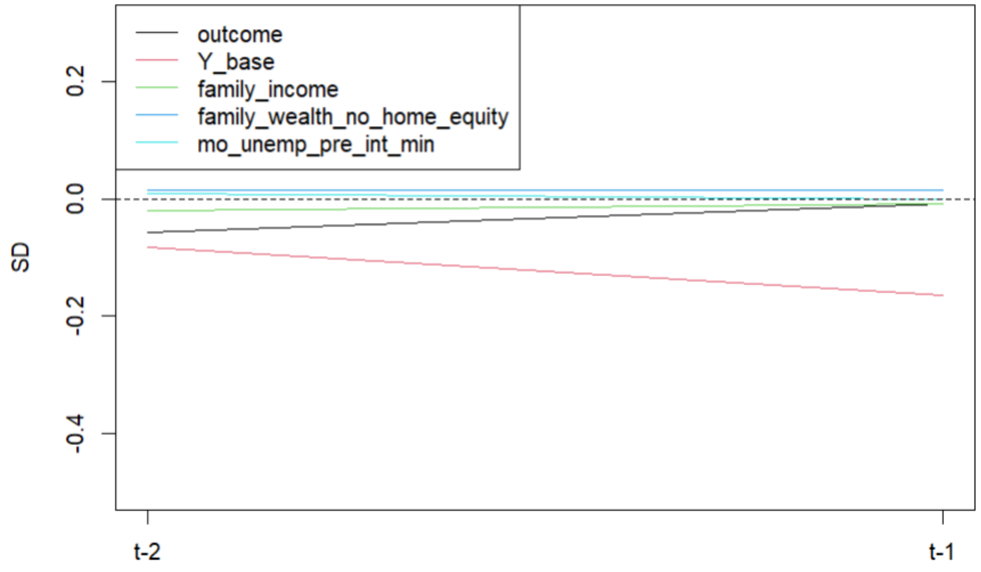
Parallel Trends Assumption Pre-Post Refining

We rely on the parallel trends assumption pre-exposure. Below shows the standardized deviation in mean covariate differences between newly unemployed and consistently employed observations over time for continuous variables (family income, family wealth, months unemployed pre-interview, baseline EQ, and subsequent EQ). We observe small differences between exposure groups before and after refinement, with better balance after refinement.

Pre-Refinement



Post-Refinement



Preliminary Results (Complete Case)

<u>Overall</u>

Comparing two populations matching in 4-year employment history, the ATT of becoming unemployed on earliest subsequent EQ when re-employed is:

Exposed Group		ATT/CATT	SE	Bootstrap 95% CI
All unemployed		-0.61	0.02	-0.65, -0.57
UI Category	No UI	-0.44	0.02	-0.49, -0.39
	UI (Any)	-1.14	0.08	-1.29, -0.98
	UI (< Median Max Dur.)	-1.29	0.40	-2.18, -0.68
	UI (≥ Median Max Dur.)	-1.13	0.08	-1.28, -0.99
	UI (< Median Max Ben.)	-1.11	0.14	-1.39, -0.85
	UI (≥ Median Max Ben.)	-1.16	0.09	-1.34, -0.97

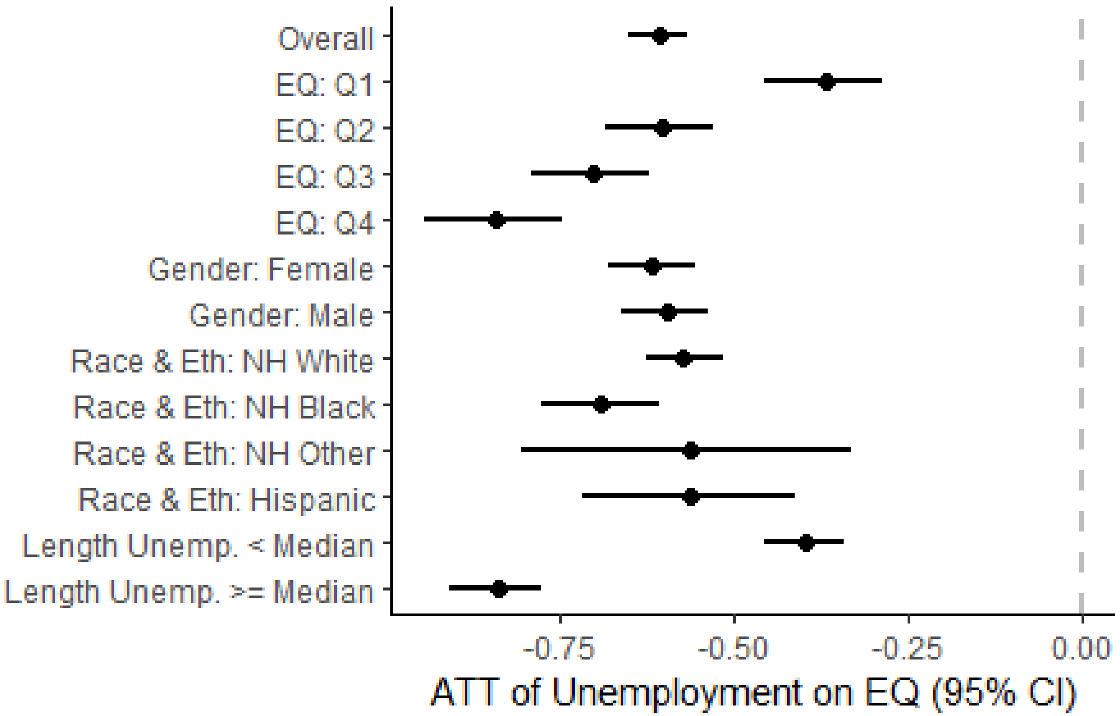
Median Maximum Duration: 26 weeks. Median Maximum Benefit with Dependents: $390/week.

Preliminary Results (Complete Case)

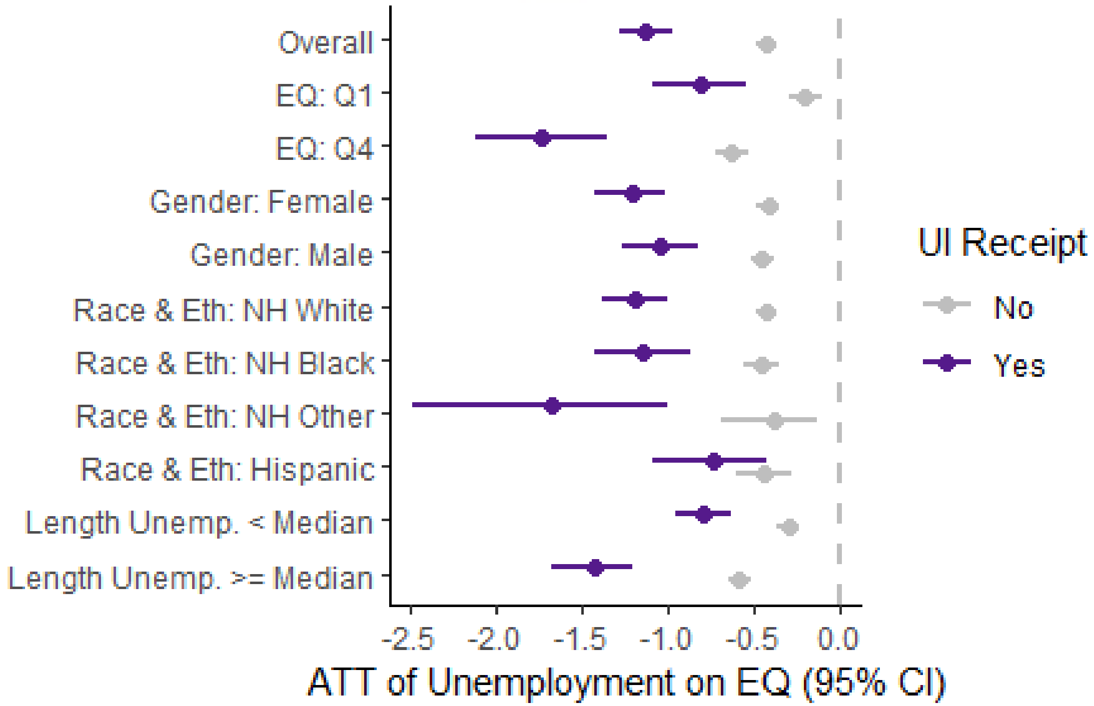
Comparing Subpopulations

Comparing two populations matching in 4-year employment history, the ATT of becoming unemployed on earliest subsequent EQ when re-employed is:

Scarring Effects



UI Modification



Preliminary Results (Multiply Imputed)

Overall

Comparing two populations matching in 4-year employment history, the ATT of becoming unemployed on earliest subsequent EQ when re-employed is:

Exposed Group		Pooled ATT	Pooled SE	Pooled 95% CI
All unemployed		-0.56	0.02	-0.61, -0.52
UI Category	No UI	-0.51	0.02	-0.55, -0.46
	UI (Any)	-0.94	0.07	-1.08, -0.81
	UI (< Median Max Dur.)	-0.82	0.44	-1.68, 0.03
	UI (≥ Median Max Dur.)	-0.95	0.07	-1.09, -0.81
	UI (< Median Max Ben.)	-0.83	0.12	-1.08, -0.59
	UI (≥ Median Max Ben.)	-1.01	0.09	-1.18, -0.84

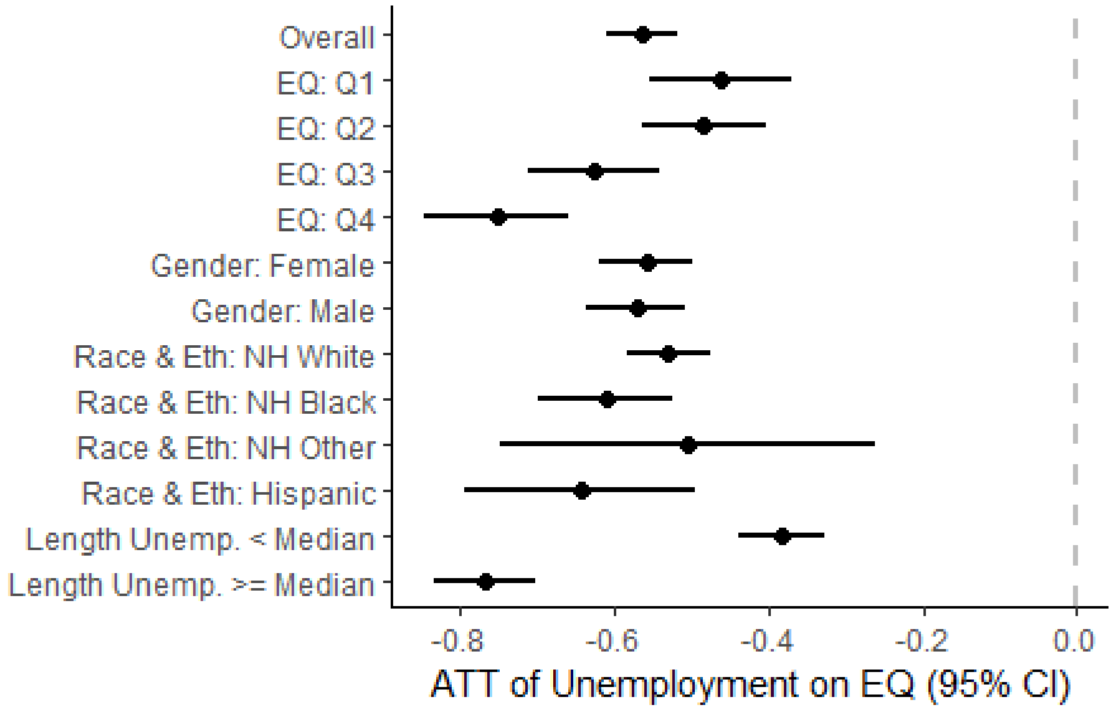
Median Maximum Duration: 26 weeks. Median Maximum Benefit with Dependents: $390/week.

Preliminary Results (Multiply Imputed)

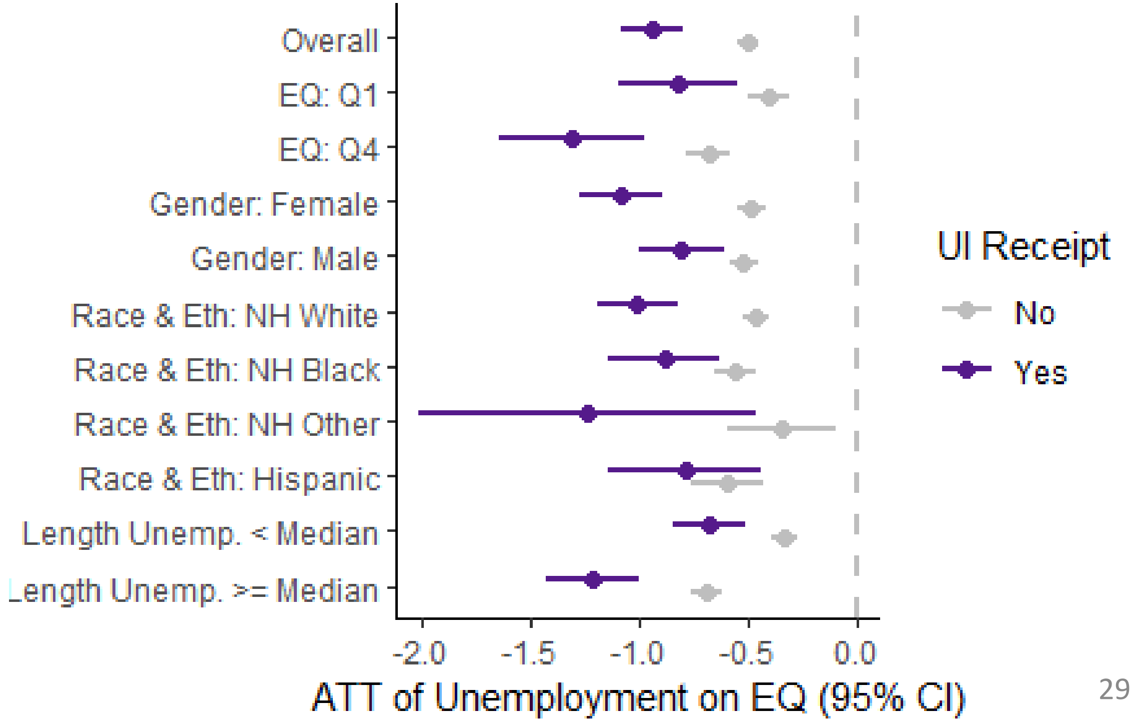
Comparing Subpopulations

Comparing two populations matching in 4-year employment history, the ATT of becoming unemployed on earliest subsequent EQ when re-employed is:

Scarring Effects



UI Modification



Preliminary Conclusions

Scarring Effects

- Becoming unemployed causes significant declines in multi-dimensional EQ upon re-employment.
- These effects are more pronounced for those with better initial EQ, those non-Hispanic Black or Hispanic, and those remaining unemployed for longer, though scarring effects do not vary considerably by gender overall.

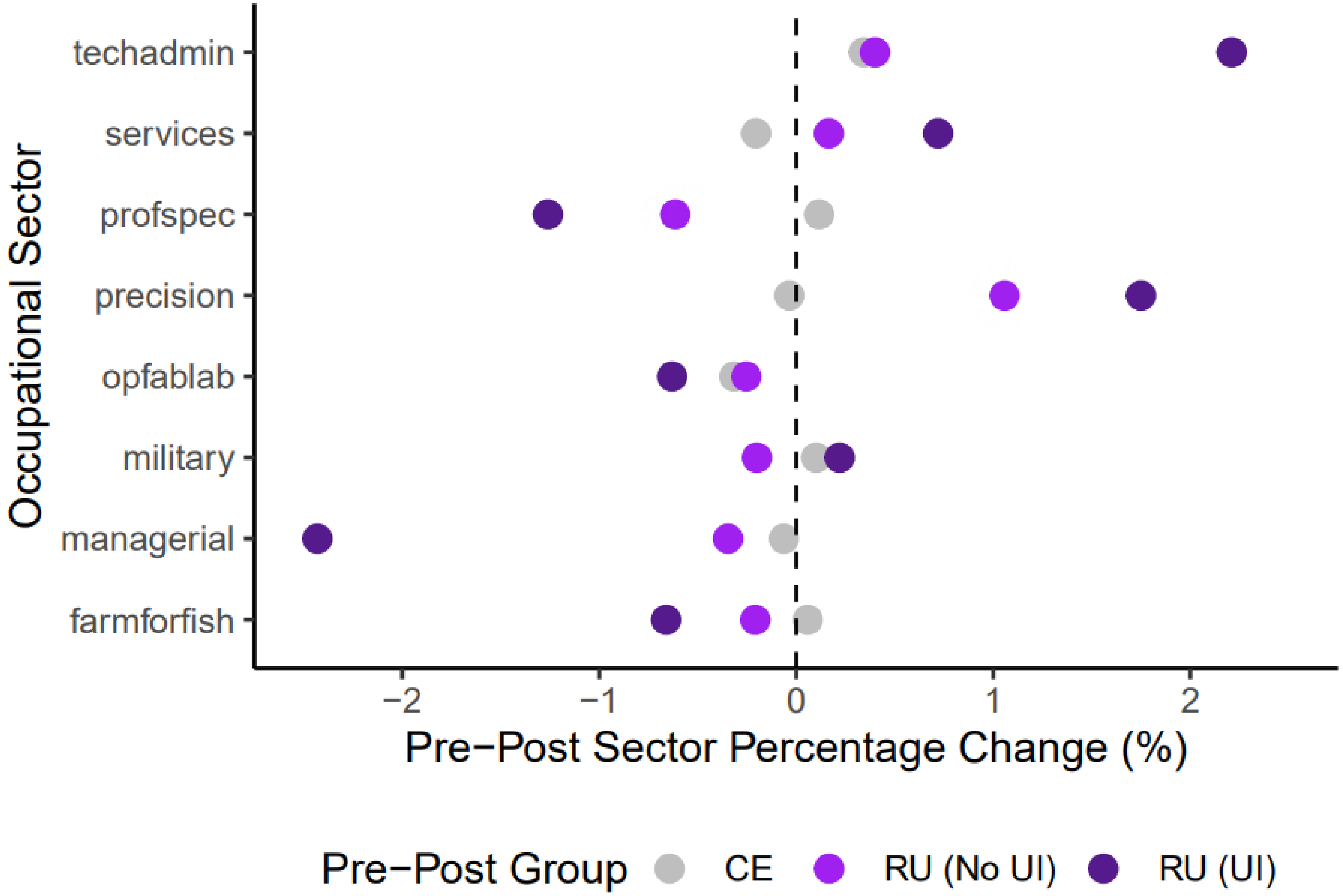
Modification of Scarring Effects by Unemployment Insurance Receipt

- The effects of becoming unemployed on subsequent EQ are more detrimental for those receiving UI, especially for recipients in states with longer-lasting and more generous UI policies.
- The negative modification associated with UI receipt appears greatest for those with better initial EQ, for men, for those non-Hispanic white or non-Hispanic and not white or Black (i.e. ‘other’), and for those remaining unemployed for longer.

Selection Effects in a Complete-Case Analysis

- Relying on a complete-case analysis would have minimized the estimated scarring effects experienced for those Hispanic, and suggested scarring effects are more detrimental for those receiving UI in states with shorter-lasting UI policies, though would not have inferentially changed other findings.

Preliminary Conclusions



Occupational Sector Key: ‘techadmin’ = Technical sales and admin support. ‘profspec’ = Professional specialty. ‘precision’ = Precision production, craft and repair. ‘opfablab’ = Operators, fabricators & laborers. ‘farmforfish’ = Farming, forestry, fishing.