Does Federally-Funded Job Training Work? Non-experimental Estimates of WIA Training Impacts Using Longitudinal Data on Workers and Firms

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Introduction

Thanks for inviting me!

Thanks to NSF for funding this

Where do papers come from? This one comes from an unexpected email from Harry Holzer

Very big picture

Evaluation policy for ALMPs: choosing institutions and a data collection strategy to make evaluation possible or not; see e.g. Smith (2011), Smith and Sweetman (2010)

Northern Europe: do high quality non-experimental data using detailed, high quality, administrative data on populations

US: do occasional randomized experiments and supplement with medium-quality evaluations using less detailed, medium quality administrative data

Canada: avoid experiments at all costs; instead, rely on a mix of survey data (with suspicious response rates) and administrative data (without much temporal detail or many covariates)

This paper: in the US context, can we produce more credible and useful estimates by using existing, but not previously utilized, administrative data sources in a non-experimental evaluation?

Another very big picture: cumulating knowledge about conditioning variables

Evaluations of ALMPs that use administrative data often rely on a "selection on observed variables" evaluation strategy

This raises the challenge of determining which variables are required for this identification strategy to produce valid estimates

This is not, sadly, how much of the literature frames the question; instead we get papers on whether matching "works" rather than what variables you need to make it work

But see Lechner and Wunsch (2013), Jacob, Ludwig and Smith (TBA) and Caliendo and Mitnik (2013)

Literature (abbreviated)

Mueser, Troske and Garislovsky (2007)
JTPA non-experimental evaluation using state administrative data

Hollenbeck, Schroeder, King and Huang (2005); Hollenbeck (2009)
WIA non-experimental evaluation using state administrative data

Heinrich, Mueser, Troske, Jeon and Kahvecioglu (2013)
WIA version of MTG (2007)

Dolton and Smith (1999 / 2014)
NDLP; dynamic treatment issues matter; more on flexible conditioning on pre-program outcomes

WIA Gold Standard Experiment (WGSE)
Currently in process … what will the answer be?

Contributions of this paper

Substantive: examine determinants of training receipt conditional on enrollment

Methodological: examine value of firm characteristics as conditioning variables

Substantive: examine value of firm characteristics as outcomes

Methodological: examine alternative sets of conditioning variables

Methodological: examine alternative estimators based on the CIA

Methodological: compare CIA and BSA

Noble, pure and good: (almost a partial) replication of Heinrich et al. (2013)

Workforce Investment Act Program

The latest in the sequence of major federally funded employment and training programs in the US, following MDTA, CETA and JTPA

Federal funding with decentralized operation at the state and local – Workforce Investment Board (WIB) level

Substantively important and poorly designed performance management system similar to that under JTPA. See Barnow (2011) and Heckman et al. (2011)

⇨ Cream-skimming and other behavior likely important

Adult and dislocated worker (= recently lost a job) funding streams

Not a huge program by historical standards, but lots of $$ during recession

Workforce Investment Act Program (continued)

Service mix similar to JTPA (and to Canada and the UK etc.):

Training (lasts at most four quarters, usually less)
Classroom training in occupational skills ("individual training accounts")
Subsidized on-the-job training at private firms (sometimes = wage subsidy)

Intensive (usually shorter and less intense than training)
Comprehensive assessment, counseling, career planning and short courses

Core (short, low intensity)
Counseling, job search assistance and placement, LMI

One-stop centers

Pyramid power

What we estimate and why we estimate it

We estimate the impact of receiving WIA training (plus possibly also core and/or intensive services) relative to receiving only core and/or intensive services

Why we estimate this:

1. It is interesting and policy relevant

2. The problem of selection is arguably less difficult than WIA / no-WIA because everyone we look at selected into WIA

3. Timing issues are lessened relative to WIA / no-WIA

This is just a subset of what is estimated in e.g. Heinrich et al. (2013)

We originally planned to do much more than this, but this has taken 10 years.

Model(s)

Participation without timing: Heckman and Robb (1985), Heckman, LaLonde and Smith (1999)

This model gives you the dip and motivates conditioning set

Participation with timing: McCall, Smith and Wunsch (2016)

Whom to serve: Heckman et al. (2011) *Performance of Performance Standards* book, Heckman, Smith and Taber (1996) “Corpus Christi” paper

Related empirics: Lechner and Smith (2007), Bell and Orr (2002)

DATA - LEHD

Linked employer-employee data; also linked to other Census products

Must be used at secure Census Research Data Center (RDC)

Employee data is from state unemployment insurance records

- ⇨ No government or informal jobs are covered
- ⇨ Quarterly timing, no hours information, no wage information

We have 25 quarters of UI data for each registrant: 12 quarters before and 12 quarters after registration

Firm data is for firms, not establishments (but 70% at one-establishment firm)

Data: WIASRD

WIASRD = WIA Standard Record Data

WIA registration start and stop dates (but …)
WIB location
Demographics (age, education, race, sex, disabled, veteran etc.)
Services received (with start and stop dates in State A)
Some matched UI earnings outcomes for performance management

Noisy and messy, as such data sets usually are

WIASRD and LEHD matched with SSNs (= SINs)

Data: states

We use data from two anonymous states

State A: medium Atlantic seaboard state
State B: large Midwestern state

Our two states are too shy to have our impact estimates attached to them by name

Ten or so other states declined our offer of a free evaluation of their WIA programs. Could there be principal-agent problems?

Heinrich et al. (2013) were able to get more states because they had the blessing of the U.S. Department of Labor (but still only got 12 of 50)

Data: time and sample sizes

WIA registrants in 2000-2005

State A
Adults: 16,144
    Training: 4679
Dislocated workers: 11,136
    Training: 4387

State B
Adults: 23,377
    Training: 11,478
Dislocated workers: 28,484
    Train: 16,323

These are large sample sizes. The NJS had 20,601 in the experiment, of whom about 2/3 were in the treatment group.

Determinants of training: propensity score models

Model 1: inspired by Dehejia and Wahba (1999, 2002)

Model 2: an approximation to the model in Heinrich et al. (2013)
    In a spirit of replication but without the WIB indicators

Model 3: Model 2 plus WIB (i.e. location) indicators
    Inspired by Heckman et al. (1998)'s finding about local labor markets

Model 4: Model 3 + firm variables
    This is why we got the LEHD!

Model 5: Model 3 + more lagged labor market outcomes
    Does Heinrich et al. (2013) go back far enough?

Model 6: Model 3 + firm variables plus more lagged labor market outcomes
    One grand propensity score model

Determinants of training, propensity score models (continued)

Correlation between Model 1 and Model 2 ranges from 0.68 to 0.88

Correlations between Model 1 and Models 3-6 range from 0.37 to 0.61

Correlations between Model 2 and Models 3-6 range from 0.55 to 0.71

Correlations among Models 3, 4, 5 and 6 all exceed 0.99

This will have implications for the comparisons of the propensity score models!

Identification

Cross-section estimates require the Conditional Independence Assumption (CIA)

The literature is clear on the value of basic demographics, including age, sex, race and education. We have those.

The literature is clear on the importance of lagged outcomes, at a reasonable level of temporal detail and conditioned on flexibly. We have that in Models 2-6.

The firm variables may contain information on worker characteristics that do not show up in the demographics or (less obviously) in the earnings and employment histories

Be nice to have ability and non-cognitive skills and more detail on pre-program human capital, such as high school grades and quality and college major, grades and quality. But will these all show up in earnings? See e.g. Caliendo and Mitnik (2013) and Lechner and Wunsch (2013).

Identification (continued)

Difference-in-differences estimates require the (conditional) Bias Stability Assumption (BSA)

See HIST (1998) and also Rosenbaum (2001)

How well does flexible conditioning on the pre-program outcomes capture any time-invariant differences?

Estimation: OLS estimators

1. Pooled OLS with an indicator for treatment
Motivation: simple as can be, pleasantly retro

2. OLS on untreated units only; use predicted values as counterfactuals
Motivation: still really simple, unlike pooled OLS it estimates ATET; see Angrist (1998) and Angrist and Pischke (2009)

3. Pooled median regression with an indicator for treatment
Motivation: examine sensitivity to outliers

Estimation: Nearest neighbor(u)r matching

We apply the estimator with 1, 3 and 5 neighbo(u)rs

The comparison group is larger than the treatment group which suggests that a wider bandwidth (i.e. 3 or 5 neighbo(u)rs) will reduce MSE

Nearest neighbor(u)r matching sucks in all Monte Carlo analyses – see e.g. Frölich (2004), Busso, DiNardo and McCrary (2013) and Huber, Lechner and Wunsch (2013)

But low bias combined with high variance and insensitivity to extreme propensity scores $\Rightarrow$ good complement to IPW

But still the most commonly applied estimator in the literature and so worth looking at

Estimated standard errors are, for the moment, incorrect.

Estimation: inverse propensity weighting (IPW)

$$\hat{\Delta}_{TT} = \frac{1}{n_1}\sum_{i=1}^{n} Y_i D_i - \frac{1}{n_0}\sum_{i=1}^{n}\left(\frac{1}{n_0}\sum_{i=1}^{n}\frac{\hat{P}(X)(1-D_i)}{1-\hat{P}(X)}\right)^{-1}\frac{\hat{P}(X_i)Y_i(1-D_i)}{1-\hat{P}(X_i)}$$

IPW generally performs well in Monte Carlo analyses so long as the weights are forced to sum to one in the sample; see Frölich (2004) and Busso, DiNardo and McCrary (2013)

Originally developed in the statistics literature to do deal with survey non-response; see Horvitz and Thompson (1952) *JASA*

A close cousin to DiNardo, Fortin and Lemieux (1996) *Econometrica*

Estimated standard errors are, for the moment, incorrect.

Outcome variables

<u>Usual suspects:</u>
1. UI earnings by calendar quarter relative to the quarter of WIA registration
2. Employment (i.e. UI earnings > 0) by calendar quarter relative to registration

<u>Cool, new firm outcomes</u>
3. 1/0 High LEHD firm fixed effect (good)
4. 1/0 No LEHD firm fixed effect (bad)
5. Continuous firm fixed effect
6. 1/0 Firm size > 100 (good)
7. 1/0 High turnover firm (bad)
8. 1/0 Switched industries (ambiguous but interesting)

Outcomes 3, 4 and 6-8 include the non-employed as zeros and use all observations

Outcome 5 codes the non-employed as missing and uses only the employed

TABLE 2a: Descriptive Statistics for Earnings & Employment, State A

	Adult				Dislocated			
	Treated		Untreated		Treated		Untreated	
Number of Participants	4640		10892		4347		6489	
	Earnings	Employment	Earnings	Employment	Earnings	Employment	Earnings	Employment
t-12	3120	0.57	3117	0.55	6408	0.72	6406	0.70
t-11	3248	0.58	3173	0.56	6718	0.74	6670	0.72
t-10	3223	0.59	3271	0.57	6760	0.74	6853	0.73
t-9	3391	0.60	3353	0.58	6993	0.75	7064	0.74
t-8	3386	0.61	3341	0.59	7059	0.76	7120	0.74
t-7	3549	0.62	3472	0.61	7309	0.78	7491	0.78
t-6	3518	0.63	3480	0.61	7461	0.80	7632	0.79
t-5	3559	0.63	3544	0.61	7644	0.81	7865	0.80
t-4	3558	0.64	3431	0.62	7753	0.82	7766	0.81
t-3	3557	0.64	3218	0.60	7806	0.83	7723	0.81
t-2	3364	0.63	3018	0.59	7449	0.80	7558	0.80
t-1	2877	0.60	2682	0.58	6610	0.75	6576	0.73
t	1942	0.55	2150	0.64	3985	0.57	3845	0.58
t+1	2072	0.58	2879	0.69	2658	0.49	3758	0.60
t+2	2796	0.65	3353	0.70	3457	0.60	4883	0.69
t+3	3381	0.68	3575	0.70	4228	0.65	5390	0.72
t+4	3678	0.69	3631	0.69	4713	0.68	5479	0.71
t+5	3875	0.70	3754	0.68	4921	0.69	5668	0.71
t+6	4092	0.70	3714	0.67	5271	0.70	5783	0.71
t+7	4109	0.69	3777	0.67	5381	0.71	5859	0.70
t+8	4137	0.68	3801	0.66	5439	0.70	5811	0.70
t+9	4196	0.68	3838	0.66	5507	0.70	5951	0.69
t+10	4247	0.68	3811	0.65	5591	0.70	5967	0.69
t+11	4259	0.67	3881	0.64	5681	0.70	6021	0.68
t+12	4286	0.66	3902	0.64	5644	0.69	5978	0.68

Source: Authors' calculations from WIA and LEHD data.
Notes: Earnings are in 2008$. Employment is proportion employed.

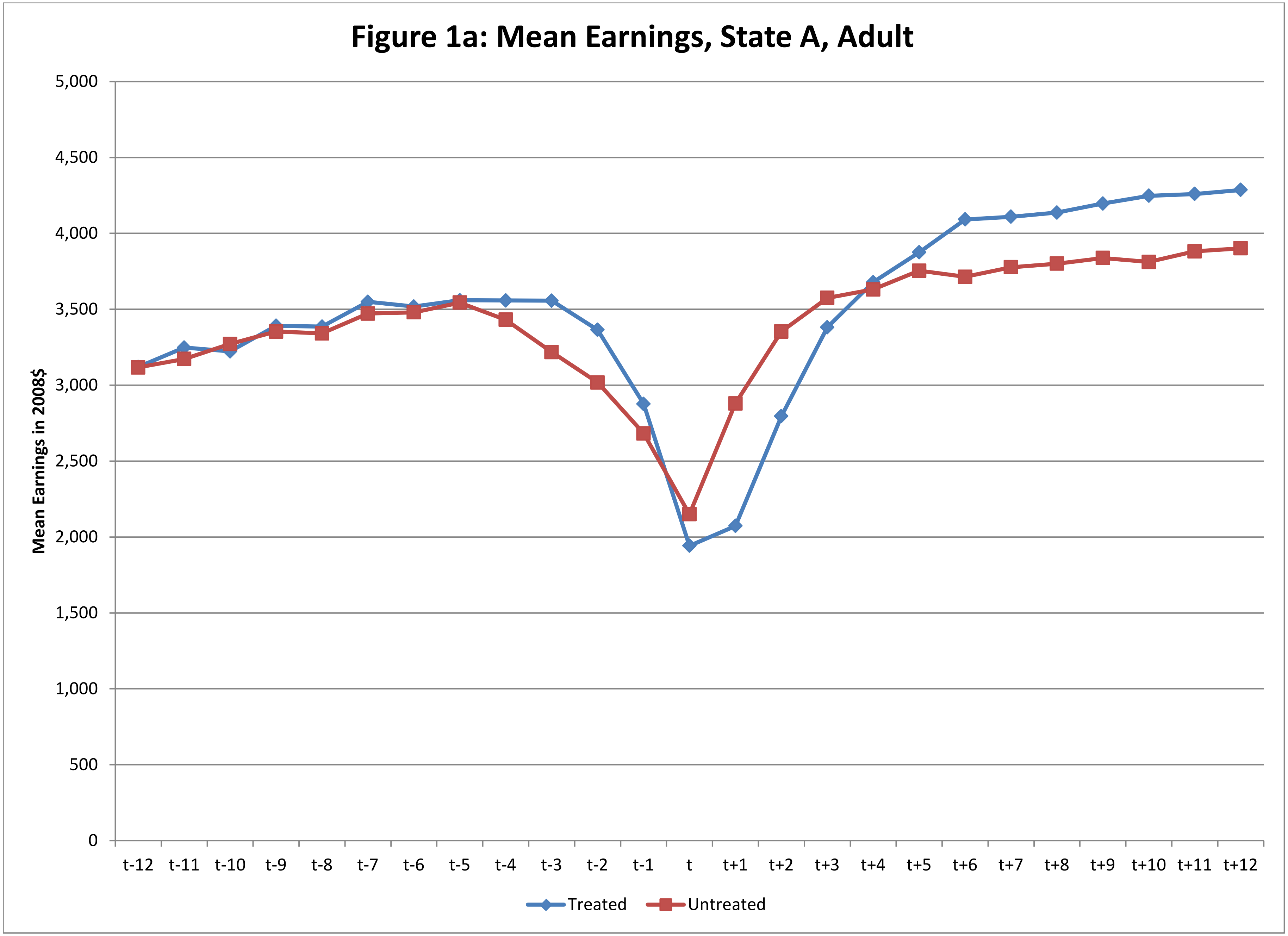
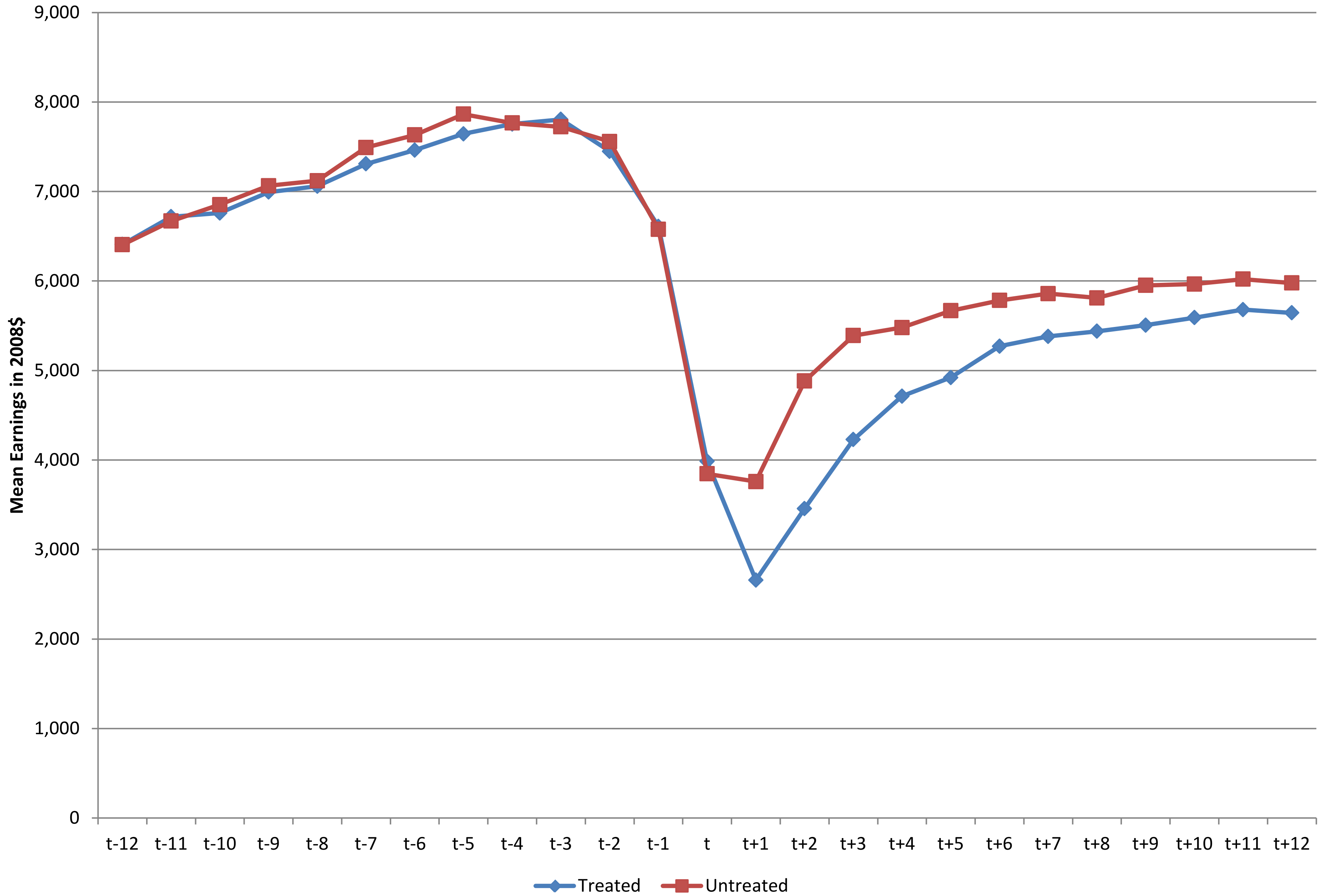


Figure 1a: Mean Earnings, State A, Adult
Mean Earnings in 2008$
5,000
4,500
4,000
3,500
3,000
2,500
2,000
1,500
1,000
500
0
t-12
t-11
t-10
t-9
t-8
t-7
t-6
t-5
t-4
t-3
t-2
t-1
t
t+1
t+2
t+3
t+4
t+5
t+6
t+7
t+8
t+9
t+10
t+11
t+12
Treated
Untreated

Figure 1b: Mean Earnings, State A, Dislocated



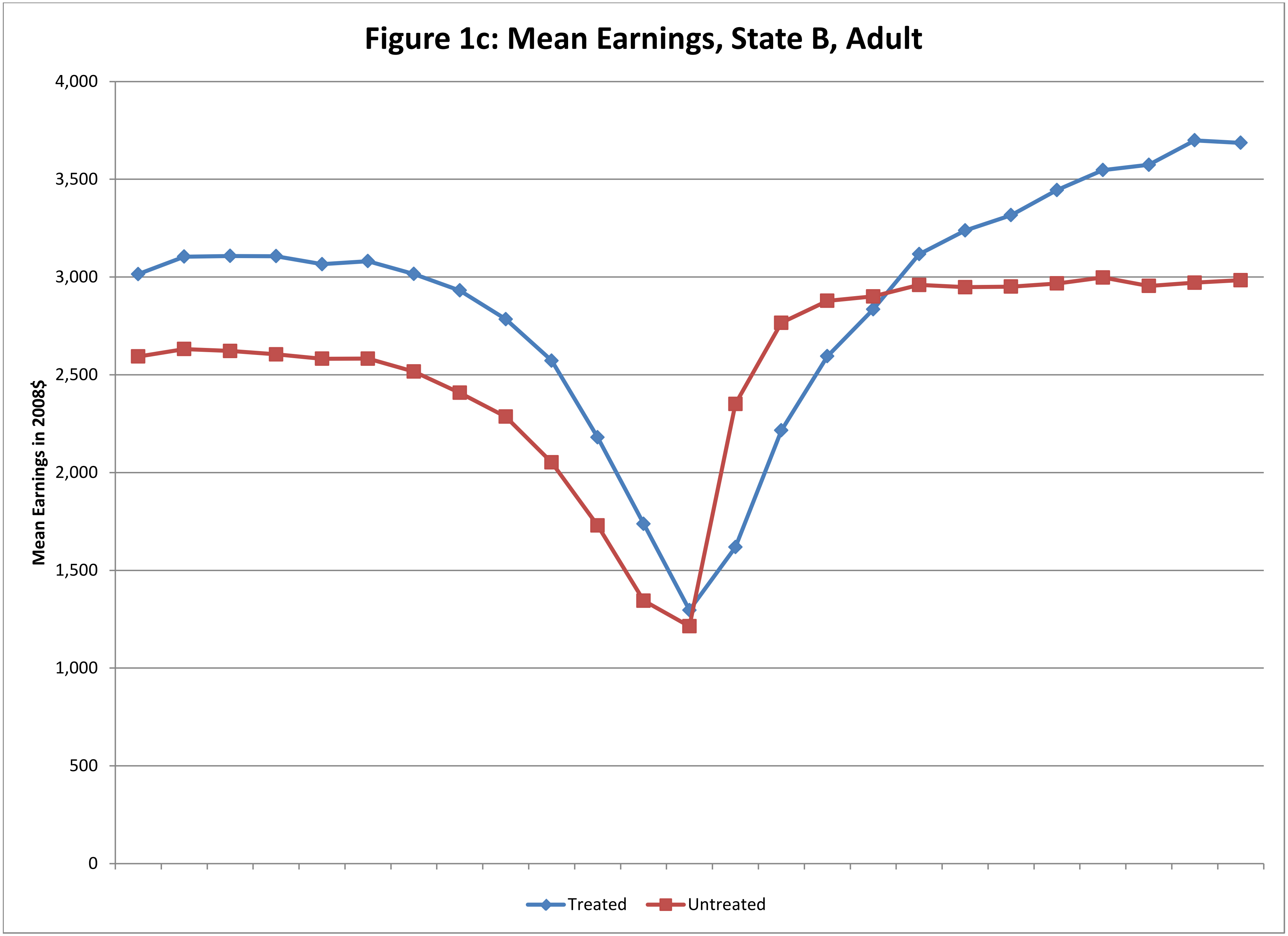


Figure 1c: Mean Earnings, State B, Adult
Mean Earnings in 2008$
4,000
3,500
3,000
2,500
2,000
1,500
1,000
500
0
Treated
Untreated

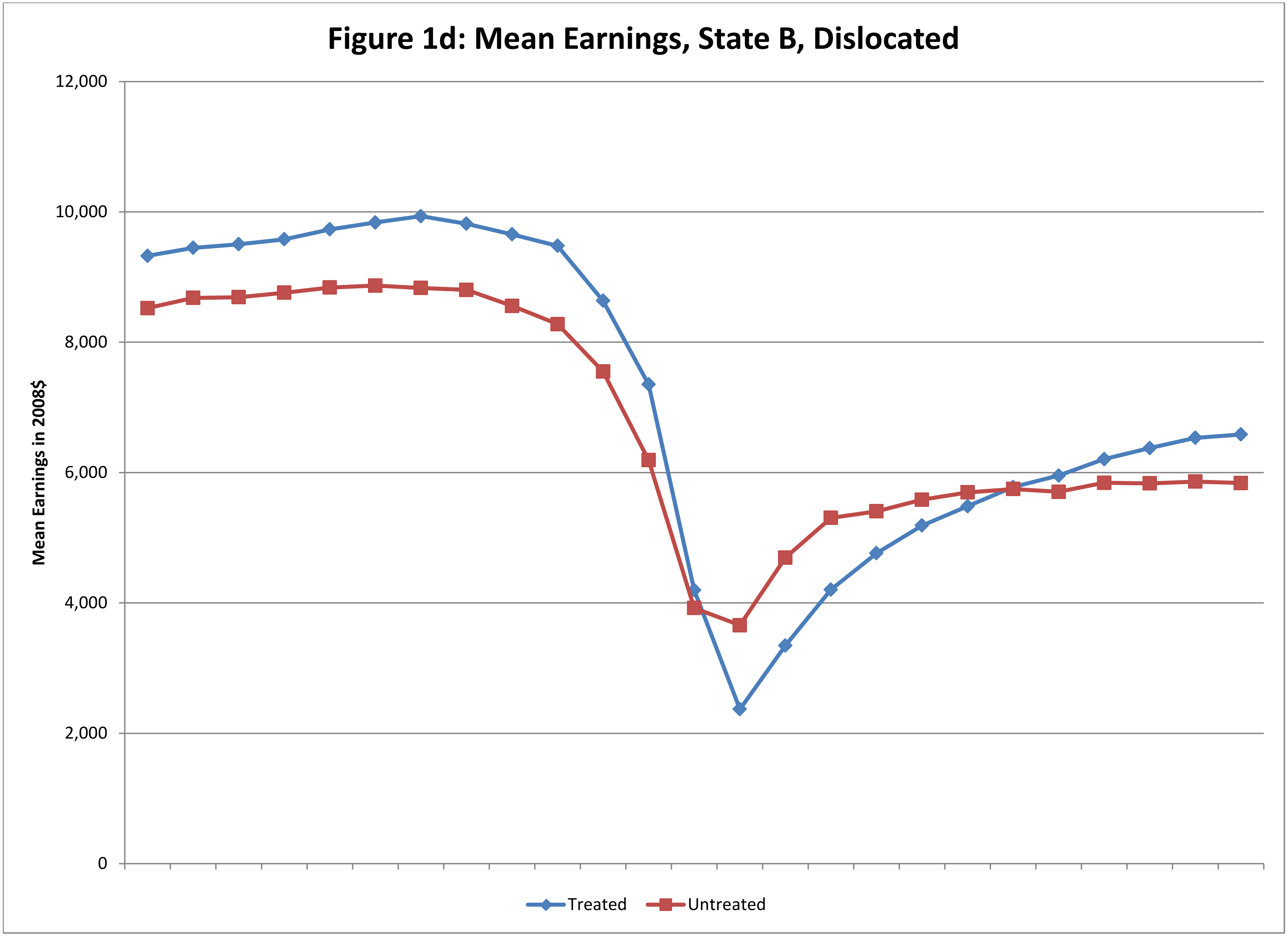


Figure 1d: Mean Earnings, State B, Dislocated
Mean Earnings in 2008$
12,000
10,000
8,000
6,000
4,000
2,000
0
Treated
Untreated

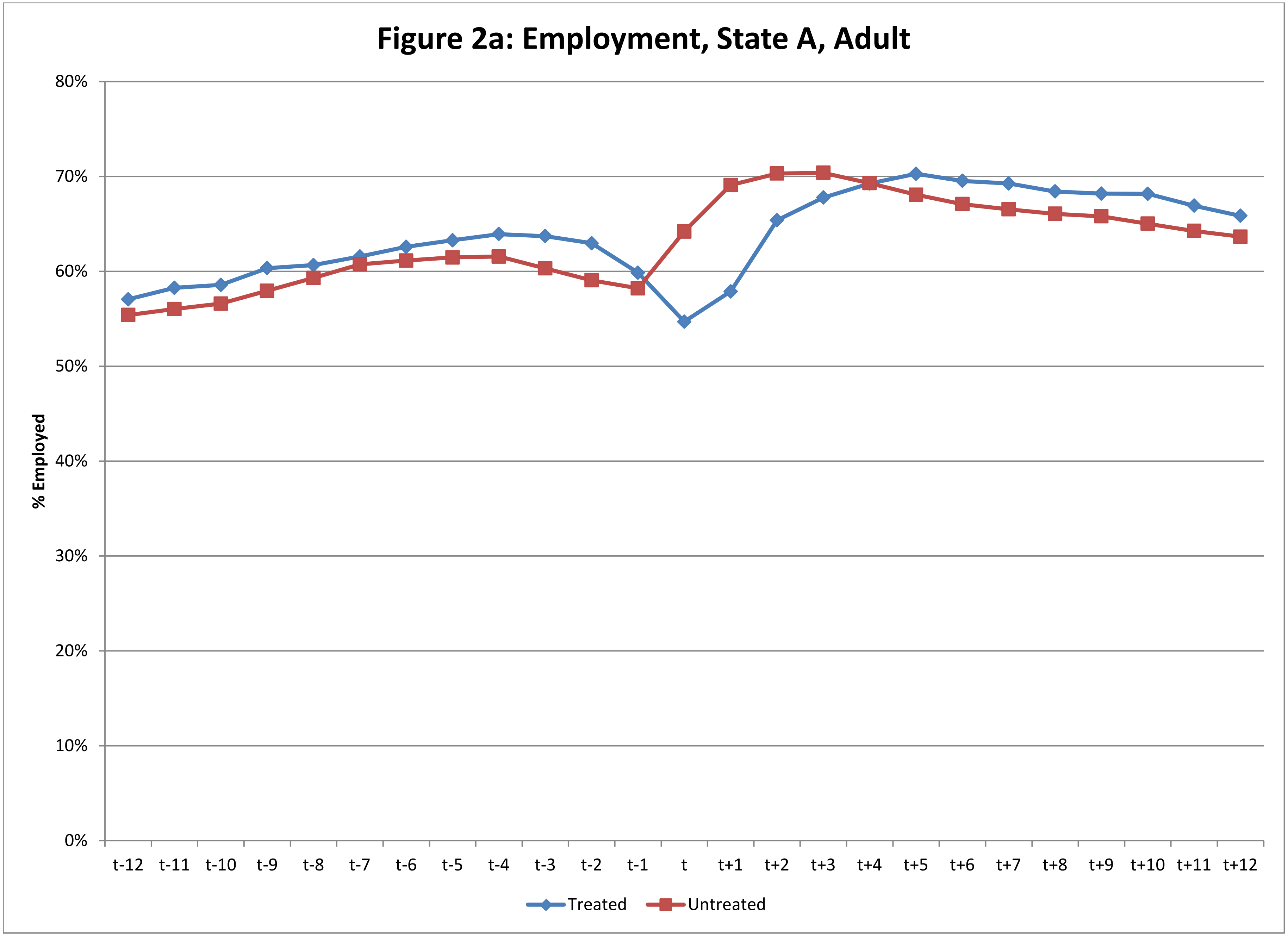


Figure 2a: Employment, State A, Adult
% Employed
80%
70%
60%
50%
40%
30%
20%
10%
0%
t-12
t-11
t-10
t-9
t-8
t-7
t-6
t-5
t-4
t-3
t-2
t-1
t
t+1
t+2
t+3
t+4
t+5
t+6
t+7
t+8
t+9
t+10
t+11
t+12
Treated
Untreated

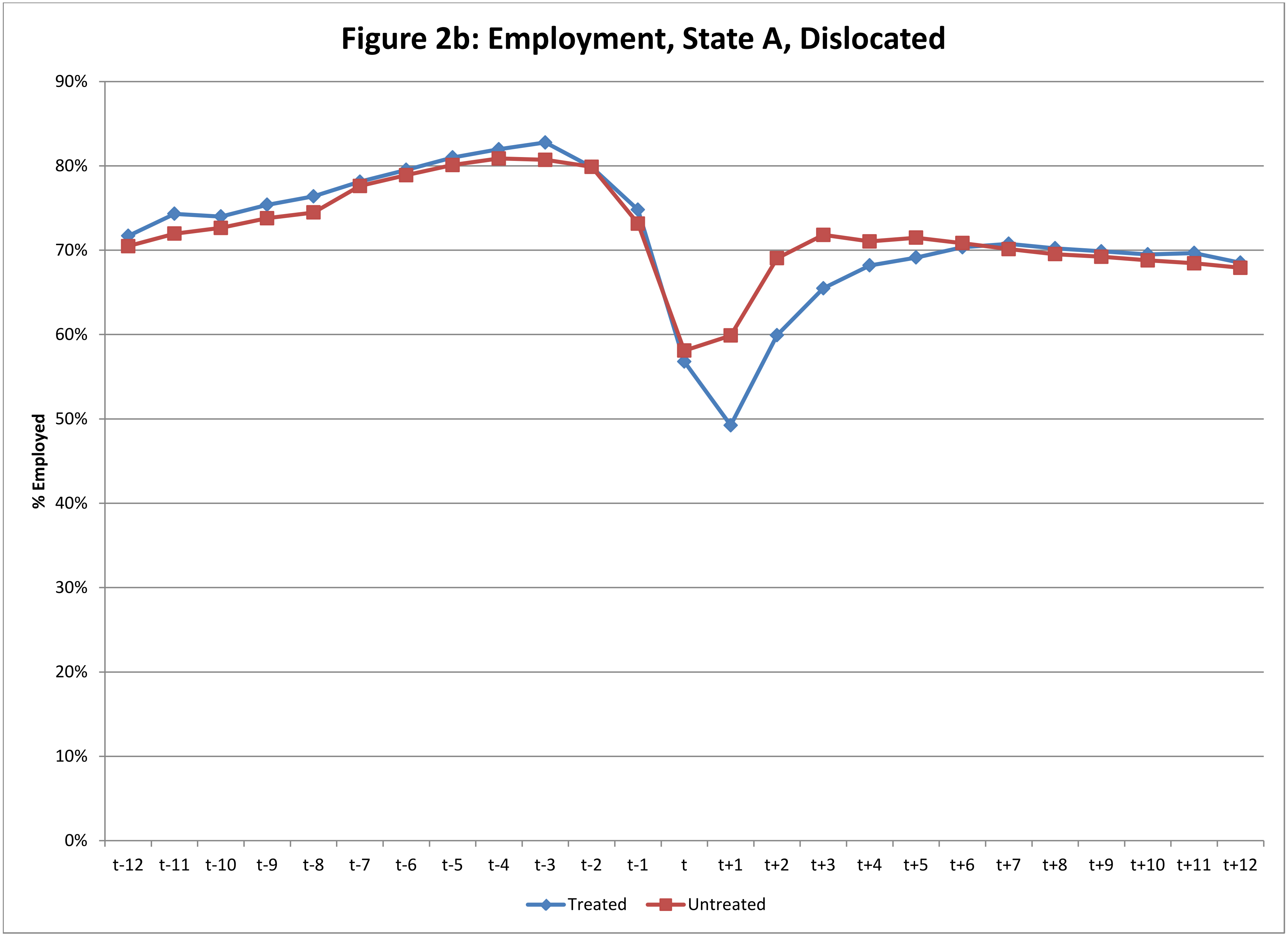
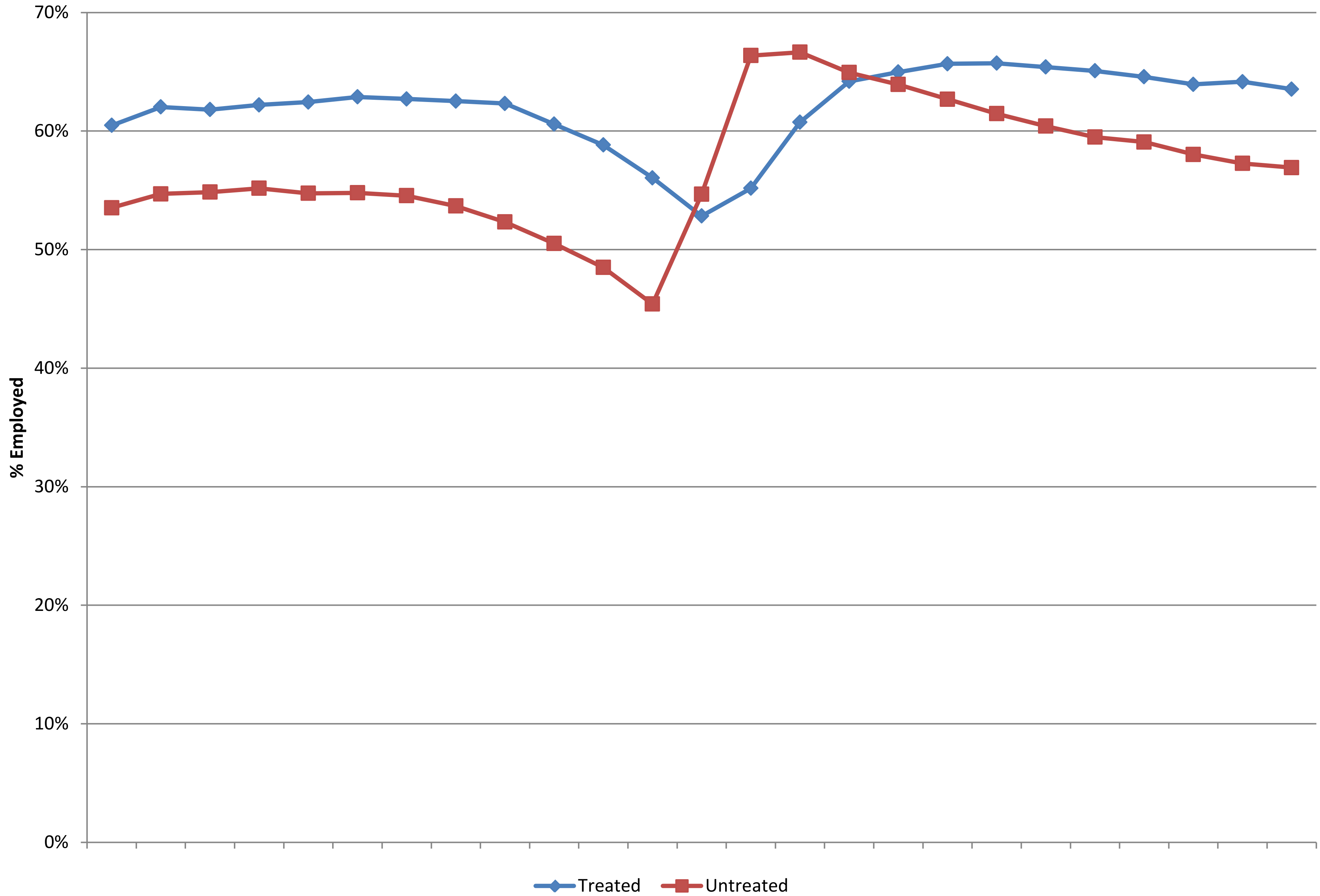


Figure 2b: Employment, State A, Dislocated
% Employed
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
t-12
t-11
t-10
t-9
t-8
t-7
t-6
t-5
t-4
t-3
t-2
t-1
t
t+1
t+2
t+3
t+4
t+5
t+6
t+7
t+8
t+9
t+10
t+11
t+12
Treated
Untreated

Figure 2c: Employment, State B, Adult



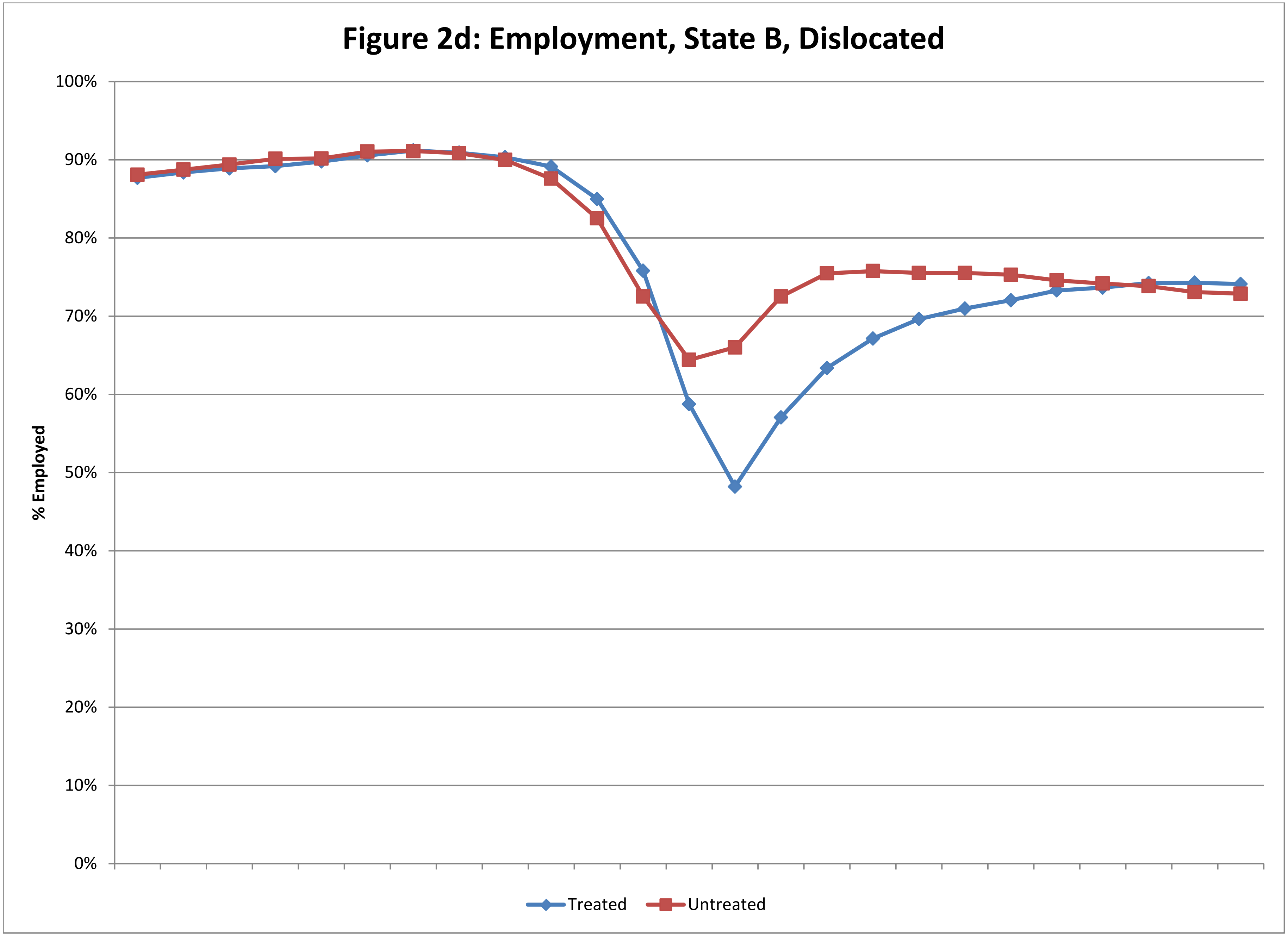


Figure 2d: Employment, State B, Dislocated
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
% Employed
Treated
Untreated

Results: earnings

Lock-in effects are important

About four quarters for adults

At least two years for displaced workers

Substantial impacts for adults in the third year out; about \$1250 in State A and about \$1700 in State B

Third year impacts for dislocated workers vary by state; State A shows a negative impact about -\$900 but State B shows a positive impact of \$815

Few differences between men and women ⇒ pool in other tables

Our results are broadly similar to those in Heinrich et al. (2013) and in Hollenbeck (2009)

Why are the impacts so different by funding stream?

TABLE 4a: Impacts on Earnings & Employment, Inverse Propensity Score Weighting, Model 6, State A

	Adult Classification			Dislocated Classification		
	Treatment Effect	Standard Error	P-value	Treatment Effect	Standard Error	P-value
Earnings, Differences						
t+1	-597	55	<.0001	-939	104	<.0001
t+2	-464	59	<.0001	-1121	102	<.0001
t+3	-276	67	<.0001	-969	105	<.0001
t+4	-39	67	0.597	-546	104	<.0001
t+5	-11	69	0.887	-478	105	<.0001
t+6	214	74	0.009	-281	112	0.014
t+7	245	69	0.001	-180	110	0.103
t+8	274	70	0.000	-154	112	0.174
t+9	304	72	0.000	-491	161	0.002
t+10	393	72	<.0001	-155	114	0.179
t+11	261	74	0.001	-123	124	0.330
t+12	299	75	0.000	-129	118	0.281
Total, t+1 to t+12	602	641	0.387	-5567	1047	<.0001
Total, t+9 to t+12	1257	270	<.0001	-899	447	0.045
Employed						
t+1	-0.070	0.008	<.0001	-0.067	0.010	<.0001
t+2	-0.030	0.008	0.000	-0.055	0.009	<.0001
t+3	-0.013	0.007	0.121	-0.030	0.009	0.001
t+4	-0.003	0.007	0.729	-0.001	0.009	0.886
t+5	0.012	0.007	0.126	0.009	0.009	0.316
t+6	0.022	0.007	0.007	0.026	0.009	0.004
t+7	0.021	0.007	0.009	0.043	0.009	<.0001
t+8	0.007	0.007	0.366	0.039	0.009	<.0001
t+9	0.018	0.008	0.032	0.035	0.009	0.000
t+10	0.028	0.008	0.001	0.036	0.009	<.0001
t+11	0.018	0.008	0.028	0.051	0.009	<.0001
t+12	0.022	0.008	0.008	0.037	0.009	<.0001

Source: Authors' calculations from WIA and LEHD data.

Results: job characteristics

Firm size: small positive effects in both states for adults, but small negative effects for dislocated workers

High turnover firm: not much for adults or dislocated workers in State A, but small positive effects on dislocated workers in State B

High fixed effect firm: not much in State A, small positive effect on adults in State B but small negative effect on dislocated workers in State B

Results: job characteristics (continued)

Switched industry:

State A: no effects for adults, around 0.05 for dislocated workers

State B: around 0.05 for adults and 0.06 for dislocated workers

Employment: modest employment effects for both states and funding streams

State A: adults about 0.02, displaced workers about 0.05

State B: adults about 0.04, displaced workers about 0.01

Continuous fixed effect conditional on employment:

Not much for either state or funding stream

TABLE 6a: Impacts on Firm Characteristics, Inverse Propensity Score Weighting, Model 6, State A

	Adult Classification			Dislocated Classification		
	Treatment Effect	Standard Error	P-value	Treatment Effect	Standard Error	P-value
High Fixed Effect						
t+12	0.006	0.007	0.401	-0.001	0.008	0.892
No Fixed Effect						
t+12	0.008	0.006	0.186	0.010	0.007	0.179
Continuous Fixed Effect						
t+12	0.003	0.005	0.477	-0.011	0.005	0.053
Firm Size >= 100						
t+12	0.005	0.009	0.637	-0.015	0.011	0.167
High Turnover						
t+12	-0.009	0.008	0.301	0.006	0.009	0.481
Switched Industry						
t+12	-0.001	0.009	0.909	0.054	0.010	<.0001

Source: Authors' calculations from WIA and LEHD data.

Results: sensitivity to conditioning variables

DW specification is very different than the rest

But WIA training should be an easier selection problem than NSW

Firm variables make some difference relative to Model 3 (see Model 4), but not much relative to Model 5 (see Model 6). Are the firm variables worth it?

Additional year of earnings does not add much.

Geography less important here than in HIST – compare Models 2 and 3 – but not forcing exact matches here as in HIST

TABLE 8a: Impacts on Earnings, Inverse Propensity Score Weighting, Alternative Conditioning Variables, State A

	Adult Classification			Dislocated Classification		
	Treatment Effect	Standard Error	P-value	Treatment Effect	Standard Error	P-value
Combined change over t+1 through t+12						
Model 1	-1703	655	0.016	-8819	1024	<.0001
Model 2	-603	648	0.388	-8994	1025	<.0001
Model 3	622	641	0.371	-5671	1047	<.0001
Model 4	626	641	0.368	-5544	1048	<.0001
Model 5	596	641	0.391	-5679	1047	<.0001
Model 6	602	641	0.387	-5567	1047	<.0001
Combined change over t+9 through t+12						
Model 1	502	274	0.093	-1777	431	<.0001
Model 2	747	272	0.012	-2048	433	<.0001
Model 3	1277	270	<.0001	-935	449	0.038
Model 4	1263	270	<.0001	-901	448	0.045
Model 5	1270	270	<.0001	-927	447	0.039
Model 6	1257	270	<.0001	-899	447	0.045

Source: Authors' calculations from WIA and LEHD data.

Results: BSA versus CIA

Only very modest differences between estimates based on the CIA and those based on the conditional bias stability assumption

This implies that our flexible conditioning on the pre-program outcomes does a good job of picking up any time-invariant differences

TABLE 9a: Differences-in-Differences Impacts on Earnings, Inverse Propensity Score Weighting, Model 6, State A

		Adult Classification			Dislocated Classification		
		Treatment Effect	Standard Error	P-value	Treatment Effect	Standard Error	P-value
Differences-in-Differences, t+1 to t+12							
Difference in	Prior Earnings	-128	722	0.872	-2562	1273	0.047
	Total Change	729	738	0.373	-3005	1329	0.026
	t+1	-587	69	<.0001	-726	125	<.0001
	t+2	-453	70	<.0001	-908	125	<.0001
	t+3	-266	75	0.001	-756	127	<.0001
	t+4	-29	74	0.728	-332	126	0.010
	t+5	0	76	0.999	-264	126	0.041
	t+6	224	79	0.011	-68	130	0.613
	t+7	255	74	0.002	33	129	0.801
	t+8	285	76	0.001	59	129	0.653
	t+9	315	77	0.000	-278	175	0.104
	t+10	403	76	<.0001	59	132	0.662
	t+11	271	78	0.002	90	141	0.531
	t+12	310	79	0.000	84	135	0.540
Differences-in-Differences, t+9 to t+12							
Difference in	Prior Earnings	-81	273	0.787	-807	475	0.093
	Total Change	1337	321	0.000	-92	568	0.873
	t+9	324	85	0.001	-290	185	0.109
	t+10	413	84	<.0001	47	143	0.748
	t+11	281	86	0.003	79	152	0.612
	t+12	319	86	0.001	73	146	0.625

Source: Authors' calculations from WIA and LEHD data.
Notes: For differences-in-differences analysis, the pre-period is t-12 through t-1 when using t+1 to t+12 as the post-period, and is t-12 through t-9 when using t+9 through t+12 as the post-period.

Results: sensitivity to estimator choice

The results are not very sensitive to the choice of estimator

Because the correct standard errors are still in process, MSE comparisons are not that helpful at this point

Dynamic treatment effects: results

Dynamic treatment issues turned out not to matter much in this context because most of those who receive training do so within one or two quarters of enrollment

Cost / benefit analysis

See the discussion in Section 10.2 of Heckman, LaLonde and Smith (1999)

Key issue: costs
WIA knows very little about its cost structure, unlike Farrell's Ice Cream Parlor
The cost difference between our treatments is likely $2,500-$7,500

Key issue: duration of benefits
The JTPA literature – see U.S. GAO (1996) – suggests at least some persistence, as does the NSW literature, but GAIN and Job Corps both fade out

Key issue: discount rates
Key issue: marginal social cost of public funds
Key issue: general equilibrium effects – see Lamadon et al. (2014)
Key issue: other outcomes (e.g. child outcomes, crime)

TABLE 9a: Cost-Benefit Analysis, State A

Benefit Duration	MSCPF	Annual Discount Rate	Net Benefit per Participant: $2500 Direct Costs: Adult	$2500 Direct Costs: Dislocated	$7500 Direct Costs: Adult	$7500 Direct Costs: Dislocated
As Long as in the Data						
	1.00	0	-1898	-8067	-6898	-13067
	1.00	0.05	-2057	-7925	-7057	-12925
	1.00	0.1	-2209	-7787	-7209	-12787
	1.25	0	-2523	-8692	-8773	-14942
	1.25	0.05	-2682	-8550	-8932	-14800
	1.25	0.1	-2834	-8412	-9084	-14662
	1.50	0	-3148	-9317	-10648	-16817
	1.50	0.05	-3307	-9175	-10807	-16675
	1.50	0.1	-3459	-9037	-10959	-16537
5 Years						
	1.00	0	80	-10059	-4920	-15059
	1.00	0.05	-415	-9594	-5415	-14594
	1.00	0.1	-859	-9173	-5859	-14173
	1.25	0	-545	-10684	-6795	-16934
	1.25	0.05	-1040	-10219	-7290	-16469
	1.25	0.1	-1484	-9798	-7734	-16048
	1.50	0	-1170	-11309	-8670	-18809
	1.50	0.05	-1665	-10844	-9165	-18344
	1.50	0.1	-2109	-10423	-9609	-17923
Indefinite						
	1.00	0	+inf	-inf	+inf	-inf
	1.00	0.05	19491	-23333	14491	-28333
	1.00	0.1	6951	-14338	1951	-19338
	1.25	0	+inf	-inf	+inf	-inf
	1.25	0.05	18866	-23958	12616	-30208
	1.25	0.1	6326	-14963	76	-21213
	1.50	0	+inf	-inf	+inf	-inf
	1.50	0.05	18241	-24583	10741	-32083
	1.50	0.1	5701	-15588	-1799	-23088

Source: Authors' calculations from WIA and LEHD data.
Notes: Estimates are drawn from Table 4. With an annual discount rate of 0, the benefits under the assumption of indefinite benefit duration become infinite, whether positive ("+inf") or negative ("-inf"). Costs are assumed to entirely occur in the first quarter after WIA registration. MSCPF is the marginal social cost of public funds.

TABLE 9b: Cost-Benefit Analysis, State B

			Net Benefit per Participant			
			$2500 Direct Costs		$7500 Direct Costs	
Benefit Duration	MSCPF	Annual Discount Rate	Adult	Dislocated	Adult	Dislocated
As Long as in the Data						
	1.00	0	-2170	-7727	-7170	-12727
	1.00	0.05	-2362	-7733	-7362	-12733
	1.00	0.1	-2545	-7736	-7545	-12736
	1.25	0	-2795	-8352	-9045	-14602
	1.25	0.05	-2987	-8358	-9237	-14608
	1.25	0.1	-3170	-8361	-9420	-14611
	1.50	0	-3420	-8977	-10920	-16477
	1.50	0.05	-3612	-8983	-11112	-16483
	1.50	0.1	-3795	-8986	-11295	-16486
5 Years						
	1.00	0	39	-8369	-4961	-13369
	1.00	0.05	-541	-8319	-5541	-13319
	1.00	0.1	-1058	-8263	-6058	-13263
	1.25	0	-586	-8994	-6836	-15244
	1.25	0.05	-1166	-8944	-7416	-15194
	1.25	0.1	-1683	-8888	-7933	-15138
	1.50	0	-1211	-9619	-8711	-17119
	1.50	0.05	-1791	-9569	-9291	-17069
	1.50	0.1	-2308	-9513	-9808	-17013
Indefinite						
	1.00	0	+inf	+inf	+inf	+inf
	1.00	0.05	26842	6236	21842	1236
	1.00	0.1	9871	-1797	4871	-6797
	1.25	0	+inf	+inf	+inf	+inf
	1.25	0.05	26217	5611	19967	-639
	1.25	0.1	9246	-2422	2996	-8672
	1.50	0	+inf	+inf	+inf	+inf
	1.50	0.05	25592	4986	18092	-2514
	1.50	0.1	8621	-3047	1121	-10547

Source: Authors' calculations from WIA and LEHD data.
Notes: Estimates are drawn from Table 4. With an annual discount rate of 0, the benefits under the assumption of indefinite benefit duration become infinite, whether positive ("+inf") or negative ("-inf"). Costs are assumed to entirely occur in the first quarter after WIA registration. MSCPF is the marginal social cost of public funds.

Conclusions: substantive

We replicate the findings in Heinrich et al. (2013) and Hollenbeck (2009), though with somewhat smaller magnitudes

My conjecture: the impacts are still a bit too big for adults and too small for displaced workers due to residual selection

WIA training (relative to core/intensive services) is much more effective for adults than for displaced workers – but why?

WIA training effects differ surprisingly little between men and women

We find non-trivial impacts of WIA training on firm characteristics, but worry about general equilibrium effects

Conclusions: methodological

DW conditioning variables do not do the job in the WIA context

Diff-in-diff results not very different from levels results, which implies that our conditioning variables do a good job of capturing time invariant differences

Conditioning on firm characteristics does not add much

Conditioning on local office does not add much

Details of the matching / weighting estimator do not matter that much to the estimates; the patterns that emerge are as expected

DTE issues are not important here due to the observed timing behavior

Results robust to various sensitivity analyses