Appendix for
"Privatizing Participation"

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This is the appendix for "Privatizing Participation" by Jane Gingrich and Sara Watson, published in the journal *Politics & Society*. It discusses the sample construction; the estimation strategy employed in the paper, as well as robustness checks.

Constructing the Sample

We faced a number of choices in constructing the sample for our analysis. A brief overview of the issues and data sources employed is provided here.

Identifying Individuals Participating in PTW

As discussed in the main paper, privatization affected all new and repeat customers starting a spell of Incapacity Benefit (IB), Severe Disablement Allowance (SDA), Income Support for reason of Disability (IS) and Employment Support Allowance (ESA) as of December 2007. Our difference-in-difference design required that we identify individuals entering these programs in always-public regions and in eventually private regions prior to and after 2007.

For the pre-period (before any privatization was implemented), our sample included all individuals who started a non-Pathways to Work (i.e., non-conditional) version of one of the four benefits mentioned above. For the post-period (that is, after privatization was initiated), our sample included all individuals who entered the conditional Pathways to Work program between 2008 and July 2010. We used this cutoff in the post-period because after this point it seems plausible that voters might face greater confusion about how to attribute responsibility for the program which had been initiated by a Labour government but was continued by the coalition Lib/Tory government. Information about which benefit an individual was contained in the variable *ficode*. We used the panel nature of the data to identify when an individual was in year 1 or 2 of benefit receipt.

Identifying individuals on IB, SDA, and ESA was fairly simple—the relevant information is contained in the variable *ficode*---but the BHPS and UKHLS do not distinguish the reason for receiving Income Support. Here, using the *jbstat* variable, we excluded all individuals on IS who reported being on maternity leave, pregnant, enrolled as a student, or a lone parent (because there is an IS benefit aimed at lone parents). We considered limiting this sample only to individuals who responded to *jbstat*==long-term disabled, but chose not to do so because the BHPS and UKHLS clearly defined this variable in quite different ways. The percent responding to being LTD in the BHPS was approximately 6 percent of the sample, but only 3 percent in the UKHLS.

Because participation in PTW was required only for individuals below pensionable age, we excluded women over the age of 60 and men over the age of 65. In order to further assure that our sample included only eligible individuals, we dropped all respondents who did not respond to consecutive waves of the survey while on benefit (because we could not determine if they had gone off benefit during their hiatus from the survey and hence whether they were new vs continuous clients); the only exception here were BHPS sample members in 2009, none of whom were interviewed in that year. We similarly dropped individuals who reported a single year of SDA sandwiched between multiple years of Incapacity Benefit, which seemed highly unlikely given accession rules to SDA. Finally, we also faced the question of how to treat individuals on Employment Support Allowance (ESA), which was launched in late 2008. Although the most disabled of ESA recipients are exempted from conditional welfare-to-work obligations, the UKHLS does not contain information on whether the respondent is required to attend work-related activity groups (WRAG). Here, we follow Carter and Whitworth in keeping in our sample the lower 75 percent of ESA recipients according to their self-reported disability score.[1] It is true that more than twenty-five percent of ESA recipients and more than one-third of our overall sample reported having none of the listed disabilities. However, we also ran models including all ESA recipients, and results were substantively similar.

Identifying Public versus Private Provision

The next task we faced was to identify which regions implemented conditional reforms to disability via public versus private provision, as well as the timing of such reforms. Here, we took our information from Department of Work and Pension Guidance Manuals and working papers, which provided information on which JobCenter Plus districts implemented conditional public and then private provision. We then created a crosswalk to deal with administrative boundary changes, as JobCenter Plus districts were originally created in 2002, but were reorganized in 2004 and again in 2007-8 and 2011. We excluded all 2007 observations because by that point, everyone in public provision was also in a conditional program whereas no one in a to-be-privatized region received conditional IB. We also excluded Northern Ireland from our analysis because we were not able to identify Northern Irish JCP districts using available geographic identifiers in our survey.

Recall that our pre-2007 comparison groups included only individuals entering traditional (ie, non-conditional) public benefits; we constructed our sample this way so that we could parse out the effect of private provision from conditional welfare requirements. Because all IB programs prior to 2004 were traditionally organized, this meant that we included everyone starting IB, SDA, and IS-D between 2000 and 2003. As conditional public welfare-to-work programs began to be piloted in late 2003, in order to keep our treated and control groups facing similar programmatic requirements, we excluded the following groups. As of 2004: new and repeat entrants to PTW residing in JobCenter Plus districts of Bridgend, Rhondda Cynon and Taff, Derbyshire, Renfrewshire, Inverclyde Argyll and Bute; Essex, Gateshead and South Tyneside, Lancashire East, and Somerset. As of late 2005 new and repeat clients residing in JCP districts of Cumbria, Glasgow, Lancashire West and Tees Valley; Barnsley Rotherham and Doncaster; City of Sunderland; County Durham; Lanarkshire and East Dumbarton; Liverpool and Wirral; Greater Manchester Central; Swansea Bay and West Wales; Eastern Valleys; Greater Mersey; and Staffordshire.

JCP districts which implemented private provision after 2007 included: Birmingham and Solihull, Black Country, Central London, City and East London, Devon and Cornwall, Edinburgh and Lothian and Borders, Forth Valley, Fife and Tayside, Greater Manchester East and West, Lambeth, Southwark and Wandsworth, Lincolnshire and Rutland, Norfolk, North and Mid Wales, Nottinghamshire, South East Wales, West Yorkshire, West of England, Bedfordshire and Hertfordshire, Cambridgeshire and Suffolk, Cheshire, Halton \& Warrington, Coventry and Warwickshire, Gloucestershire, Wiltshire and Swindon, Hampshire, Kent, Leicestershire and Northamptonshire, North and North East London, North East Yorkshire and the Humber, South London, Surrey and Sussex, Berks, Bucks and Oxfordshire, The Marches, West London and West Wiltshire.

Armed with this information on the geographic rollout of public versus private provision of PTW, the next task was to link this information on public vs private provision by JCP region to geographic identifiers in our dataset. The BHPS/UKHLS did not contain geographic identifiers based on JCP districts; instead, the closest approximation was local authority districts (LADs). Fortunately, the boundaries of LADs and JCP districts overlap very well. We therefore constructed a crosswalk to match LADs to JobCentre Plus districts based on appendix 13 to http://www.publications.parliament.uk/pa/cm200102/cmselect/cmworpen/426/42602.htm.

Our data on LADs came from BHPS and UKHLS Special License Access Datasets (SN 5151 and SN 6666) available from the UK Data Archive. Due to nomenclature changes---the former used 4-digit LAD codes the latter used 9-digit codes (in use as of 2011)---we used crosswalk tables available from the ONS at http://www.ons.gov.uk/ons/guide-method/geography/products/names--codes-and-look-ups/code-history-database/index.html.

To construct our analysis dataset, we saved all observations for individuals, before and during their tenure on one of the disability benefits described above. Where possible, we kept three years of pre-disability benefit information. In order to address potential problems of serial correlation associated with panel DiD models and with our dependent variable, we follow the prescription of Bertrand, Duflo and Mullainathan, collapsing the data to two time periods, taking an individual's average value on covariates from the pre-period and their average values from the post period.[2] After differencing these pre and post observations, we were left with a dataset where for each observation we had a single (differenced) value on which we ran OLS using our DD strategy described below.

Estimation Strategy

Our paper uses two types of difference-in-difference (DD) models. For Table 1, which looked at how private provision affected `objective' quality differences (such as success in finding employment), we take all individuals starting in year 1 or year 2 of disability benefit, treating each observation in our panel dataset as arising from a pooled cross-section and estimating the difference in patterns of employment success among different groups, before and after the policy change. Thus, we formally estimate:

$$Y_{it} = \beta_0 + \beta_1 dB + \delta_0 d2 + \delta_1 d2 \cdot dB + \varepsilon$$

where Y is the outcome of interest (ie, Found Job), and $d2$ is a dummy variable for the post-privatization time period. The dummy variable dB captures possible differences between the treatment (PLP/private) and control (JCP/public) groups prior to the policy change. The time period dummy, $d2$, captures aggregate factors that would cause changes in Y, even in the absence of a policy change. The coefficient of interest, δ_1, multiplies the interaction term, $d2 \cdot dB$, which is equivalent to a dummy variable equal to 1 for those observations in the treatment (privatized) group in the post period.

The models reported in Tables 2 through 6 differ from those reported in Table 1 in that they leverage the panel nature of our data. This is because here, in contrast to the employment outcome variables, for each respondent we had information on their pre- and post-benefit attitudes, and could therefore explore how entering treatment altered these attitudes. The simplest of panel DD models involve using information on the same individuals over two time periods, so that the key difference with respect to the model discussed above is that the differences over time are for the same cross-sectional units. Here, in order to estimate the effect of private provision on political preferences, one would let it denote a binary indicator set to one if person i lived in a region with private provision at time t. Because no one participated in private provision in the initial time period, $prog_{it}$=0 for all. In the second time period, $prog_{it}$ is 1 for those who participate in private provision and zero for those who do not. One then estimates the following equation, where the effect of privatization is obtained by regressing the change in *y* (political support) on the change in *Z* and the privatization indicator:

$$\Delta y_{i2} = \theta_2 + \Delta Z_{i2\gamma} + \delta_1 priv_{i2} + \Delta u_{i2}$$

However, because we had individuals entering disability benefits in always-public and eventually-private areas over more than time periods, but privatization was implemented at a single moment in time, we instead used:

$$\Delta y_{it} = \xi_t + \Delta Z_{it}\gamma + \Delta priv_{it} + post + \delta_1 \Delta priv_{it}.post + \Delta u_{it}$$

where the program indicator is differenced along with everything else, post is a dummy equal to 1 for those observations who experience treatment in the post period, and the ξ_t are period intercepts. The effect of privatization is given by δ_1.

For all regression models reported in the paper we follow common practice and estimate with OLS because using DD models with non-linear link functions result in the violation of the parallel trends assumption.[3]

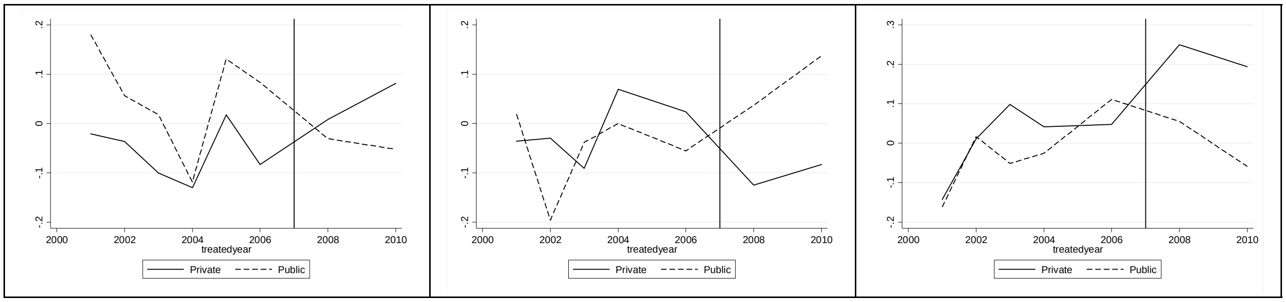
Plausibility of Underlying Assumptions in DD Models

Because the validity of the differences-in-differences estimator is based on two key assumptions—constant composition and parallel trends-- it is worth considering the plausibility of its underlying assumptions in our particular setting: the introduction of privatization in the Pathways to Work program.

The first assumption, constant composition, requires that, in the absence of treatment, the composition of treatment and control groups do not change over time. This is in part a question about the exogeneity of treatment; if some individuals can choose not to experience the treatment of privatization and if certain factors make some individuals more likely to opt out than others, this might have an effect on the accuracy of the DiD estimator. In the context of introducing private provision into the Pathways to Work program, we believe this is unlikely to be a problem. Because the onset of privatization was not widely publicized in the media, there is relatively little possibility that individuals acted strategically vis-a-vis the public vs private rollout of the program (that is, choosing not to go on IB). We also compared observable group characteristics pre- and post-treatment and found few changes over time, suggesting that unobservable characteristics are likely to be similar as well.

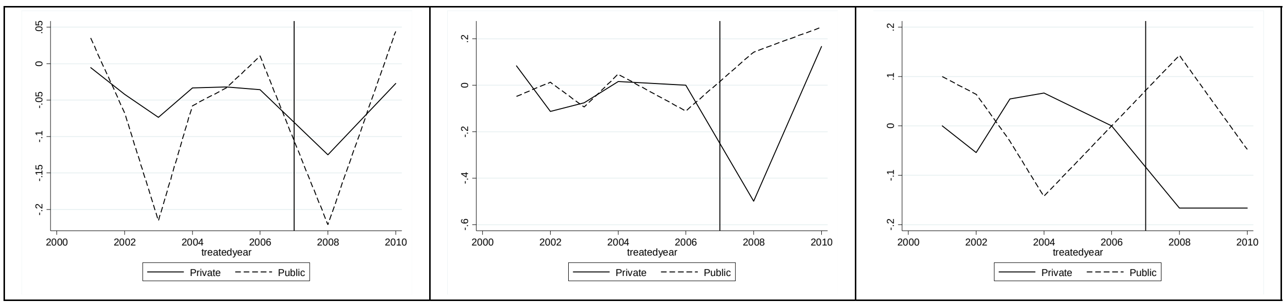
The second assumption, parallel trends, requires that the underlying trends in the outcome variable are the same for both treatment and control group. This assumption is not explicitly testable but we plotted pre- and post-time trends for both groups (reported below). Such plots are shown for disability recipients in Figures A1 through A4 below, where the red line depicts those in always-public regions and the blue line depicts those in eventually private regions. The vertical line shows the year in which privatization was instituted.

Here we see the assumption of parallel trends is generally plausible, especially for the PTW sample. Note that what is important here is that the trend remain roughly similar; the treatment and control groups may have different values in the pre-privatization period as long as they follow a broadly similar path (i.e., they are roughly parallel). As one can see, the partisan support outcomes among the disabled track each other fairly well, and then diverge in the post-treatment period. There is somewhat more jumpiness for the quality outcomes; for this reason, as we note in the paper, the regression results should be interpreted with some caution.



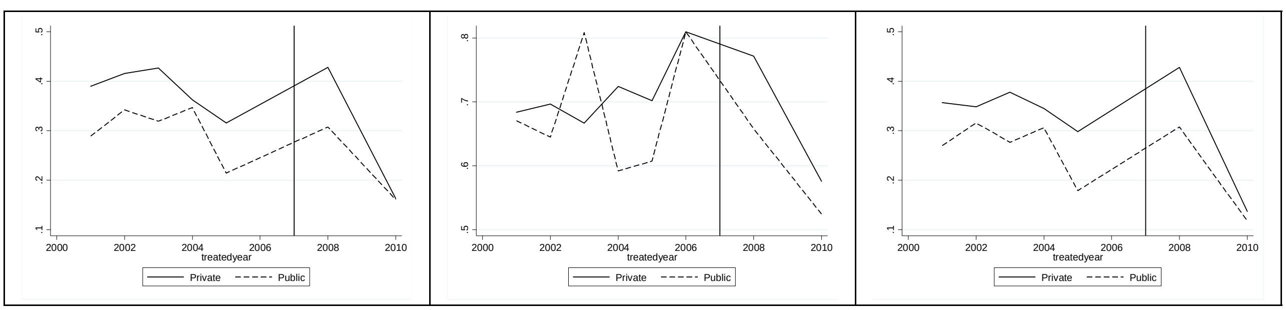
Change in Labour Support, E/W | Change in Labour Support, Scotland | Change in SNP Support

Figure A1: Assessing Parallel Trends Among the Disabled: Partisan Support



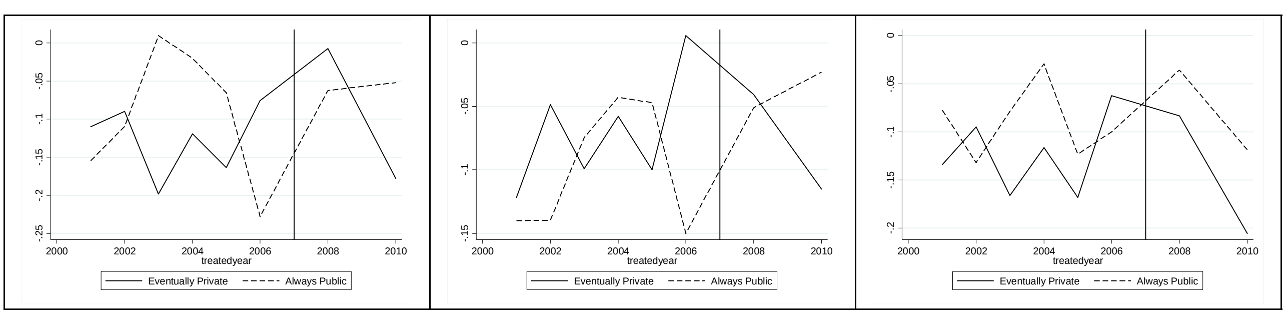
Change in Labour Support, E/W | Change in Labour Support, Scotland | Change in SNP Support

Figure A2: Assessing Parallel Trends Among the Unemployed: Partisan Support



Found Job | Off Benefit | Off Benefit, In Work

Figure A3: Assessing Parallel Trends: Objective Quality Among the Disabled



Change in Happiness | Change in Internal Efficacy | Change in External Efficacy

Figure A4: Assessing Parallel Trends: Subjective Quality Among the Disabled

Robustness

Abstention: As discussed in the paper, one possibility is that voters in England and Wales may have been punishing Labour by choosing to abstain from politics. Although we could not test this directly due to the fact that we were investigating partisan support rather than voting/turnout, we did investigate whether voters in England and Wales were more likely to support "no party." We found little evidence that this was a relevant dynamic as voters in England and Wales who experienced privatization were less likely to claim political neutrality.

Table A1: Support for No Party

	Unmatched Sample		Matched Sample	
	(1) No Party E/W	(2) No Party Scotland	(3) No Party E/W	(4) No Party Scotland
Δ PLP Participation x Post	-0.062	0.071	-0.103	0.036
	(0.06)	(0.13)	(0.07)	(0.15)
Δ PLP Participation	0.065*	-0.058	0.080**	-0.045
	(0.03)	(0.05)	(0.04)	(0.06)
Post	-0.018	0.106	0.019	0.142
	(0.07)	(0.10)	(0.08)	(0.13)
Δ HH Income	0.000	0.001	-0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Region, Year Dummies	Y	Y	Y	Y
Observations	815	221	738	197
Adjusted R^2	-0.001	0.033	0.003	0.025

Note: Year range is 2000-2010. Dependent variable is "No Party: supports no political party." All specifications report heteroskedasticity-robust standard errors clustered by district, and include dummies (not reported) for Government Office Region and the year that the respondent entered treatment.

Statistical significance: *10%; **5%; ***1%.

Source: BHPS and UKHLS, 2000-2010

Year Dummies. In the models reported in the paper, we report models which, in addition to a region dummy, also include a dummy for the year that the individual started disability benefit. One potential objection to using such dummies is that they may be collinear with the post dummy; another is that including these dummies is unnecessary given the differenced nature of the data. However, we ran all models without these dummies and results are similar with respect to both substantive and statistical significance. Results from these models are reported below, in Tables A2 through A5.

Table A2. Incumbent Labour Support, England and Wales

	Unmatched Sample		Matched Sample	
	(1) Labour Support	(2) Labour Support	(3) Labour Support	(4) Labour Support
Δ PLP Participation x Post	0.203***	0.201***	0.204***	0.203***
	(0.05)	(0.05)	(0.06)	(0.07)
Δ PLP Participation	-0.086***	-0.089**	-0.074**	-0.083**
	(0.03)	(0.04)	(0.04)	(0.04)
Post	-0.075**	-0.068	-0.073	-0.063
	(0.04)	(0.04)	(0.05)	(0.05)
Δ HH Income	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Region Dummies	N	Y	N	Y
Treatment Year Dummies	N	N	N	N
Observations	815	815	738	738
Adjusted R^2	0.017	0.015	0.018	0.018

Note: Corresponds to paper Table 3. Panel difference-in-difference estimates where the effect of privatization is indicated by the term ΔPLP Participation x Post. Dependent variables are as follows: "Supports Labour Party: change in support for the Labour Party"; All specifications report heteroskedasticity-robust standard errors clustered by district, models (2) and (4) include dummies (not reported) for Government Office Region.

Statistical significance: *10%; **5%; ***1%.

Source: BHPS and UKHLS, 2000-2010.

Table A3. Scotland vs England/Wales

	Unmatched Sample		Matched Sample	
	(1) Labour Support	(2) SNP	(3) Labour Support	(4) SNP
Δ PLP Participation x Post X Scotland	-0.374***		-0.408***	
	(0.11)		(0.13)	
Δ PLP Participation x Post	0.201***	0.094	0.203***	0.172
	(0.05)	(0.10)	(0.07)	(0.10)
Post X Scotland	0.181**		0.208	
	(0.08)		(0.11)	
Δ PLP Participation x Scotland	0.120**		0.134**	
	(0.05)		(0.07)	
Δ PLP Participation	-0.088**	0.065	-0.083**	0.038
	(0.04)	(0.04)	(0.04)	(0.04)
Post	-0.068	0.071	-0.063	-0.006
	(0.04)	(0.05)	(0.05)	(0.03)
Scotland	-0.091**		-0.102	
	(0.04)		(0.07)	
Δ HH Income	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Region Dummies	Y	Y	Y	Y
Treatment Year Dummies	N	N	N	N
Observations	1036	221	935	197
Adjusted R^2	0.012	0.019	0.015	0.012

Note: Corresponds to paper Table 4. Panel difference-in-difference estimates in which the effect of privatization is indicated by the term ΔPLP Participation x Post. Dependent variables are ``Labour Support: change in support for the Labour Party''; "SNP Support: change in support for the Scottish National Party." All specifications report heteroskedasticity-robust standard errors clustered by district and dummies (not reported) for Government Office Region.

Statistical significance: *10%; **5%; ***1%.

Source: BHPS and UKHLS, 2000-2010.

Table A4: Unemployed (JSA) Placebo

	Unmatched Sample		Matched Sample	
	(1) Labour Support	(2) Labour Support	(3) Labour Support	(4) Labour Support
Δ PLP Participation x Post	0.000	-0.000	0.024	0.019
	(0.07)	(0.07)	(0.07)	(0.07)
Δ PLP Participation	0.006	-0.007	-0.005	-0.027
	(0.03)	(0.04)	(0.04)	(0.04)
Post	-0.019	-0.028	-0.046	-0.053
	(0.05)	(0.06)	(0.06)	(0.05)
Δ HH Income	-0.001	-0.001	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Region Dummies	N	Y	N	Y
Treatment Year Dummies	N	N	N	N
Observations	614	614	588	588
Adjusted R^2	-0.005	-0.001	-0.005	-0.003

Note: Corresponds to paper Table 5. Panel difference-in-difference estimates where the effect of privatization is indicated by the term ΔPLP Participation x Post. Dependent variables are as follows: "Supports Labour Party: change in support for the Labour Party"; All specifications report heteroskedasticity-robust standard errors clustered by district, models (2) and (4) include dummies (not reported) for Government Office Region.

Statistical significance: *10%; **5%; ***1%.

Source: BHPS and UKHLS, 2000-2010.

Table A5: JSA Placebo: Scotland

	Unmatched Sample		Matched Sample	
	(1) Labour Support	(2) SNP	(3) Labour Support	(4) SNP
Δ PLP Participation X Post X Scotland	-0.300		-0.343	
	(0.19)		(0.20)	
Δ PLP Participation x Post	0.001	-0.176	0.020	-0.170
	(0.07)	(0.15)	(0.07)	(0.15)
Post X Scotland	0.246***		0.293***	
	(0.09)		(0.11)	
Δ PLP Participation X Scotland	-0.002		0.023	
	(0.06)		(0.06)	
Δ PLP Participation	-0.007	-0.027	-0.027	-0.037
	(0.04)	(0.07)	(0.04)	(0.07)
Post	-0.028	0.038	-0.053	0.036
	(0.06)	(0.06)	(0.05)	(0.07)
Scotland	-0.032		-0.013	
	(0.09)		(0.10)	
Δ HH Income	-0.000	-0.001	-0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Region Dummies	Y	Y	Y	Y
Treatment Year Dummies	N	N	N	N
Observations	774	160	732	144
Adjusted R^2	0.008	-0.003	0.007	-0.004

Note: Corresponds to paper Table 6. JSA is the unemployment benefit program in the UK. Models report panel difference-in-difference estimates, where the effect of privatization is indicated by the term ΔPLP Participation x Participation. Dependent variables are "Change in support for Labour Party"; "Change in support for SNP." All specifications report heteroskedasticity-robust standard errors clustered by district and dummies (not reported) for Government Office Region.

Statistical significance: *10%; **5%; ***1%.

Source: BHPS and UKHLS, 2000-2010.

Notes

[1] Elle Carte rand Adam Whitworth. 2013. “Creaming, Parking and Differential Payment Systems in the Work Programme: Designed Out or Designed In.” Working Paper, Department of Geography, University of Sheffield.

[2] Marianne Bertrand, Esther Duflo and Sendhil Mullainathan. 2004. “How Much Should We Trust Differences-in-Differences Estimates?” *Quarterly Journal of Economics* 119(1): 249–275.

[3] See Jeffrey M. Wooldridge 2010. *Econometric Analysis of Cross Section and Panel Data*. MIT Press for a more in-depth discussion of panel DiD models. See Michael Lechner 2011. “The estimation of causal effects by difference-in-difference methods.” *Foundations and Trends in Econometrics* 4(3): 165–224 and Susan Athey and Guido W Imbens. 2006. “Identification and Inference in Nonlinear Difference in- Difference Models.” *Econometrica* 74(2): 431–497 for discussion of the problems associated with non-linear models in DD estimation.