

A comprehensive set of postestimation measures to enrich interrupted time-series analysis

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Abstract. While the primary goal of interrupted time-series analysis (ITSA) is to evaluate whether there is a change in the level or trend of an outcome following an interruption (for example, policy change, intervention initiation), a series of additional measures may be relevant to the analysis. In this article, I seek to fill a gap in the ITSA literature by describing a comprehensive set of measures that can be computed following ITSA models, including those that fulfill the primary goal and those that provide supplementary information about trends. These measures can be calculated using the `itsa` command; this article therefore serves as a complement to “Conducting interrupted time-series analysis for single and multiple group comparisons” (Linden, 2015, *Stata Journal* 15: 480–500), which introduced the `itsa` command. Specific ITSA postestimation measures described in this article include individual trend lines, comparisons between multiple interventions, and comparisons with a counterfactual.

Keywords: `st0389_3`, `itsa`, interrupted time-series analysis, quasiexperimental designs, causal inference, counterfactual

1 Introduction

Interrupted time-series analysis (ITSA) is a suitable evaluation approach when a single unit is being studied (that is, individual, city, state, country), when the outcome variable is serially ordered as a time series, and when multiple observations are captured in both the preintervention and postintervention periods (Linden and Adams 2011; Linden 2015). The study design is called an interrupted time series because the intervention is expected to “interrupt” the level or trend of the time series, subsequent to its introduction (Campbell and Stanley 1966; Shadish, Cook, and Campbell 2002). ITSA has strong internal validity, even in the absence of a comparison group, primarily because of its control over the effects of regression to the mean (Campbell and Stanley 1966). When the treatment group’s outcomes can also be contrasted with those of one or more comparison groups, the internal validity is further enhanced by allowing the researcher to potentially control for confounding omitted variables (Linden 2015). Additionally, ITSA has strong external validity when the unit of measure is at the population level, or when the results can be generalized to other units, treatments, or settings (Shadish, Cook, and Campbell 2002; Linden, Adams, and Roberts 2004).

Linden (2015) introduced the `itsa` command, which estimates the effect of an intervention on an outcome variable for a single treatment group or when compared with one or more control groups. Its options allow the user to estimate treatment effects for multiple interventions and control for autocorrelated disturbances.

While `itsa` provides many measures of primary interest, both as part of model estimation and postestimation, investigators may find a number of additional measures helpful. The existing ITSA literature lacks guidance on computing such measures and why they may be useful. Thus, in this article, I will provide calculations for a comprehensive set of measures that an investigator may want to pursue for a study using the ITSA framework.

2 Method and formulas

Other literature has provided both a comprehensive description of the ITSA design and methodological guidance in its implementation (see Box and Tiao [1975], Glass, Willson, and Gottman [1975], and McDowall et al. [1980] for using autoregressive integrated moving-average (ARIMA) models; and see Crosbie [1993], Gottman [1981], Linden and Adams [2011], Linden [2015], McKnight, McKean, and Huitema [2000], Simonton [1977a], and Velicer and McDonald [1991] for using ordinary least-squares (OLS) regression-based models).

`itsa` relies on OLS rather than ARIMA models because the former is often more flexible and broadly applicable in an interrupted time-series context (Box et al. 2016; Velicer and Harrop 1983). Additionally, investigators trained in conventional statistical methods are generally more familiar with the OLS framework than the more complex ARIMA framework. Below I briefly describe the models for single-group and multiple-group comparisons. See Linden and Adams (2011) and Linden (2015) for a more comprehensive discussion.

2.1 The single-group analysis

When there is only one group under study (no comparison groups), and only a single treatment period, the standard ITSA regression model assumes the following form (Huitema and McKean 2000; Linden and Adams 2011; Linden 2015; Simonton 1977a; Simonton 1977b):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \epsilon_t \quad (1)$$

Y_t is the aggregated outcome variable measured at each equally spaced time point t , T_t is the time since the start of the study, X_t is a dummy (indicator) variable representing the intervention (preintervention periods 0, otherwise 1), and $X_t T_t$ is an interaction term. For a single-group study, β_0 represents the intercept or starting level of the outcome variable. β_1 is the slope or trend of the outcome variable until the introduction of the intervention. β_2 represents the change in the level of the outcome that occurs in the period immediately following the introduction of the intervention. β_3 represents the

difference between preintervention and postintervention slopes of the outcome. Thus we look for significant p -values in β_2 to indicate an immediate treatment effect or in β_3 to indicate a treatment effect over time (Linden and Adams 2011; Linden 2015).

In the model for a single treatment group exposed to a single intervention model, there are three additional measures of potential interest: the trend of the time series prior to introduction of the intervention, the trend of the time series after introduction of the time series, and the difference between the preintervention and postintervention trends. Two of these measures are part of the regression output: the preintervention trend, β_1 , and the difference between the preintervention and postintervention trends, β_3 . Thus, to measure all trend components, one needs to calculate the postintervention trend, $\beta_1 + \beta_3$.

For a second intervention, (1) is modified accordingly:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_{1t} + \beta_3 X_{1t} T_{1t} + \beta_4 X_{2t} + \beta_5 X_{2t} T_{2t} + \epsilon_t \quad (2)$$

Here X_{2t} and $X_{2t} T_{2t}$ are variables representing the additional treatment period in the study. Accordingly, β_4 represents the change in the level of the outcome that occurs in the period immediately following the introduction of the second intervention, and β_5 represents the difference between the first-intervention and second-intervention slopes of the outcome. We add corresponding X_n and $X_n T_n$ variables to the model for each additional intervention included.

In the model for a single treatment group exposed to two sequentially administered interventions, there are six measures of interest: the trends in each of the three periods (preintervention and the two intervention periods) and the differences between each period's trends (preintervention versus the first intervention, preintervention versus the second intervention, first intervention versus the second intervention). Three of these measures are provided in the regression output: the preintervention trend, β_1 ; the difference between the preintervention trend and the first-intervention trend, β_3 ; and the difference between the first- and second-intervention trends, β_5 . Thus the three remaining measures of interest that require calculation are the first-intervention period trend, $\beta_1 + \beta_3$; the second-intervention period trend, $\beta_1 + \beta_3 + \beta_5$; and the difference between the second-intervention period trend and the preintervention trend, $\beta_3 + \beta_5$.

When there is either a single treatment period or two treatment periods, the investigator may be interested in determining the counterfactual outcome, that is, the outcome at time-point T had the intervention not been introduced. As an example, assume we have a dataset containing 10 observation periods, of which the first 5 are the preintervention period and the last 5 represent the intervention period (thus 1 intervention was introduced). We calculate the predicted outcome for the actual intervention in the last (10th) observation period (although the investigator may choose any time period for comparison) using the ITSA model's parameter coefficients: $\beta_0 + (\beta_1 \times 10) + (\beta_2 \times 1) + (\beta_3 \times 4)$ (see Linden [2015] for details of the data variables corresponding to the model parameters). We calculate the counterfactual outcome for the last observation period as $\beta_0 + (\beta_1 \times 10)$. Thus, in this example, the difference in the outcome at the 10th observation period between the treatment and the counterfactual is $(\beta_2 \times 1) + (\beta_3 \times 4)$.

With additional interventions in the study, this last equation is expanded to include the corresponding X_n and $X_n T_n$ parameters.

2.2 The multiple-group analysis

When one or more control groups are available for comparison and there is only one intervention, the regression model in (1) is expanded to include four additional terms (β_4 to β_7) (Linden and Adams 2011; Linden 2015; Simonton 1977a; Simonton 1977b):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \beta_4 Z + \beta_5 Z T_t + \beta_6 Z X_t + \beta_7 Z X_t T_t + \epsilon_t \quad (3)$$

Here Z is a dummy variable denoting the cohort assignment (treatment or control), and $Z T_t$, $Z X_t$, and $Z X_t T_t$ are all interaction terms among previously described variables. The coefficients β_0 to β_3 represent the control group, and the coefficients β_4 to β_7 represent values of the treatment group. More specifically, β_4 represents the difference in the level (intercept) of the outcome variable between treatment and controls prior to the intervention, β_5 represents the difference in the slope (trend) of the outcome variable between treatment and controls prior to the intervention, β_6 indicates the difference between treatment and control groups in the level of the outcome variable immediately following introduction of the intervention, and β_7 represents the difference between treatment and control groups in the slope (trend) of the outcome variable after initiation of the intervention compared with the preintervention (Linden and Adams 2011; Linden 2015).

In this model, there are nine measures of interest: the preintervention and postintervention trends for the control group, the preintervention and postintervention trends for the treatment group, the differences in trends between groups in each period, and the differences between groups in their preintervention and postintervention trend differences (difference in differences of trends). The regression output provides four of these measures: the preintervention trend for the control group, β_1 ; the difference between the treatment and control group in their preintervention trends, β_5 ; the difference in the control group's preintervention and postintervention trends, β_3 ; and the difference in pre-post trends between the treatment and control group, β_7 (which may be considered a difference-in-differences of slopes). The five remaining measures of interest to calculate are the preintervention trend for the treatment group, $\beta_5 + \beta_1$; the control group's trend in the postintervention period, $\beta_1 + \beta_3$; the treatment group's trend in the postintervention period, $\beta_1 + \beta_3 + \beta_5 + \beta_7$; the difference between the treatment and control group's trends in the postintervention period, $\beta_5 + \beta_7$; and the difference in the treatment group's preintervention to postintervention trend, $\beta_3 + \beta_7$.

In the case of a second intervention, (2) is modified accordingly:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_{1t} + \beta_3 X_{1t} T_{1t} + \beta_4 Z + \beta_5 Z T_t + \beta_6 Z X_{1t} + \beta_7 Z X_{1t} T_{1t} + \beta_8 X_{2t} + \beta_9 X_{2t} T_{2t} + \beta_{10} Z X_{2t} + \beta_{11} Z X_{2t} T_{2t} + \epsilon_t \quad (4)$$

Here X_{2t} , $X_{2t} T_{2t}$, $Z X_{2t}$, and $Z X_{2t} T_{2t}$ are variables representing the additional treatment period in the study, and their connotation is interpreted as described in (2).

In this model containing 2 interventions, there are 18 total measures of interest: the preintervention, first-intervention, and second-intervention trends for the treatment group and the control group; the differences between groups in their trends in each of these periods, the differences between each period's trends for the treatment group and control group (preintervention versus the first intervention, preintervention versus the second intervention, first intervention versus the second intervention), and the contrast between groups for each of these periodic comparisons. The regression output provides six of these measures: the preintervention trend for the control group, β_1 ; the difference between the treatment and control group's preintervention trends, β_5 ; the control group's difference in preintervention to first-intervention trends, β_3 ; the difference between the treatment and control groups' differences in their preintervention to first-intervention trends, β_7 ; the change in the control group's first-intervention to second-intervention trends, β_9 ; and the difference between the treatment and control groups' differences in their first- to second-intervention trends, β_{11} .

The 12 remaining measures of interest for calculation are the treatment group's preintervention trend, $\beta_5 + \beta_1$; the control group's first-intervention period trend, $\beta_1 + \beta_3$; the treatment group's first-intervention period trend, $\beta_1 + \beta_3 + \beta_5 + \beta_7$; the difference between the groups in the first-intervention period, $\beta_5 + \beta_7$; the control group's trend in the second-intervention period, $\beta_1 + \beta_3 + \beta_9$; the treatment group's trend in the second-intervention period, $\beta_1 + \beta_3 + \beta_5 + \beta_7 + \beta_9 + \beta_{11}$; the difference between the groups in the second-intervention period, $\beta_7 + \beta_9 + \beta_{11}$; the treatment group's difference in trends between the preintervention and first-intervention period, $\beta_3 + \beta_7$; the treatment group's difference in trends between the first- and second-intervention periods, $\beta_9 + \beta_{11}$; the control group's difference in trends between the preintervention and second-intervention period, $\beta_3 + \beta_9$; the treatment group's difference in trends between the preintervention and second-intervention period, $\beta_3 + \beta_5 + \beta_7 + \beta_9 + \beta_{11}$; and the difference between the treatment and control group in comparing the differences in trends of the preintervention and second-intervention period, $\beta_5 + \beta_7 + \beta_{11}$.

In contrast to the single-group ITSA, where the counterfactual estimates are based solely on the treatment group's preintervention trend estimates carried forward, in a multiple-group ITSA, the control group serves as the counterfactual to the treatment group for all estimates.

3 Stata implementation of ITSA measures of interest

Stata can readily estimate all the measures of interest described in section 2 after running `itsa` using the `lincom` command, which provides point estimates as well as other important metrics, such as p -values and confidence intervals (CI). Table 1 provides a crosswalk between each measure of interest and the respective `lincom` specification after `itsa`.

Table 1. Crosswalk between model parameters and estimates following `itsa`, for all measures of interest

Measure of interest	Model parameters	lincom specification (following <code>itsa</code>)	Notes
Single group—Single intervention (1)			
Preintervention trend	β_1	<code>lincom _b[_t]</code>	In regression output
Postintervention trend	$\beta_1 + \beta_3$	<code>lincom _b[_t] + _b[_x.t(trp)]</code>	<code>itsa posttrend</code> option
Difference preintervention versus postintervention trend	β_3	<code>lincom _b[_x.t(trp)]</code>	In regression output
Single group—Comparison to counterfactual			
Counterfactual value at time-point T	$\beta_0 + \beta_1 \times T$	<code>lincom _b[_cons] + _b[_t] * T</code>	
Adjusted value for treatment at time-point T	$\beta_0 + (\beta_1 \times T) + (\beta_2 \times X) + (\beta_3 \times XT)$	<code>lincom _b[_cons] + (_b[_t] * T) + (_b[_x(trp)]) * X + (_b[_x.t(trp)]) * XT</code>	
Difference predicted versus counterfactual	$(\beta_2 \times X) + (\beta_3 \times XT)$	<code>lincom (_b[_x(trp)]) * X + (_b[_x.t(trp)]) * XT</code>	
Single group—Multiple interventions (1)			
Preintervention trend	β_1	<code>lincom _b[_t]</code>	In regression output
First-intervention trend	$\beta_1 + \beta_3$	<code>lincom _b[_t] + _b[_x.t(trp1)]</code>	<code>itsa posttrend</code> option
Second-intervention trend	$\beta_1 + \beta_3 + \beta_5$	<code>lincom _b[_t] + _b[_x.t(trp1)] + _b[_x.t(trp2)]</code>	<code>itsa posttrend</code> option
Difference preintervention versus first-intervention trend	β_3	<code>lincom _b[_x.t(trp1)]</code>	In regression output
Difference preintervention versus second-intervention trend	$\beta_3 + \beta_5$	<code>lincom _b[_x.t(trp1)] + _b[_x.t(trp2)]</code>	
Difference first- versus second-intervention trend	β_5	<code>lincom _b[_x.t(trp2)]</code>	In regression output

Continued on next page

Measure of interest	Model parameters	lincom specification (following <code>itsa</code>)	Notes
Multiple groups—Single intervention (2)			
Preintervention trend: control	β_1	<code>lincom _b[_t]</code>	In regression output
Preintervention trend: treatment	$\beta_5 + \beta_1$	<code>lincom _b[_z.t] + _b[_t]</code>	In regression output
Difference preintervention: treatment versus control	β_5	<code>lincom _b[_z.t]</code>	
Postintervention trend: control	$\beta_1 + \beta_3$	<code>lincom _b[_t] + _b[_x.t(trp)]</code>	<code>itsa posttrend option</code>
Postintervention trend: treatment	$\beta_1 + \beta_3 + \beta_5 + \beta_7$	<code>lincom _b[_t] + _b[_z.t] + _b[_x.t(trp)]</code>	<code>itsa posttrend option</code>
Difference postintervention: treatment versus control	$\beta_5 + \beta_7$	<code>lincom _b[_z.t] + _b[_z.x.t(trp)]</code>	<code>itsa posttrend option</code>
Difference preintervention versus postintervention: control	β_3	<code>lincom _b[_x.t(trp)]</code>	In regression output
Difference preintervention versus postintervention: treatment	$\beta_3 + \beta_7$	<code>lincom _b[_x.t(trp)] + _b[_z.x.t(trp)]</code>	
Difference preintervention versus postintervention: treatment versus control	β_7	<code>lincom _b[_z.x.t(trp)]</code>	In regression output
Multiple groups—Multiple interventions (2.2)			
Preintervention trend: control	β_1	<code>lincom _b[_t]</code>	In regression output
Preintervention trend: treatment	$\beta_5 + \beta_1$	<code>lincom _b[_z.t] + _b[_t]</code>	In regression output
Difference preintervention: treatment versus control	β_5	<code>lincom _b[_z.t]</code>	
First-intervention trend: control	$\beta_1 + \beta_3$	<code>lincom _b[_t] + _b[_x.t(trp1)]</code>	<code>itsa posttrend option</code>
First-intervention trend: treatment	$\beta_1 + \beta_3 + \beta_5 + \beta_7$	<code>lincom _b[_t] + _b[_z.t]</code> <code>+ _b[_x.t(trp1)] + _b[_z.x.t(trp1)]</code>	<code>itsa posttrend option</code>

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Measure of interest	Model parameters	lincom specification (following <code>itsa</code>)	Notes
Difference first intervention: treatment versus control	$\beta_5 + \beta_7$	<code>lincom _b[_z.t] + _b[_z.x.t(trp1)]</code>	<code>itsa posttrend option</code>
Second-intervention trend: control	$\beta_1 + \beta_3 + \beta_9$	<code>lincom _b[_t] + _b[_x.t(trp1)] + _b[_x.t(trp2)]</code>	<code>itsa posttrend option</code>
Second-intervention trend: treatment	$\beta_1 + \beta_3 + \beta_5 + \beta_7+ \beta_9 + \beta_{11}$	<code>lincom _b[_t] + _b[_z.t] + _b[_x.t(trp1)] + _b[_z.x.t(trp1)] + _b[_x.t(trp2)] + _b[_z.x.t(trp2)]</code>	<code>itsa posttrend option</code>
Difference second intervention: treatment versus control	$\beta_5 + \beta_7 + \beta_{11}$	<code>lincom _b[_z.t] + _b[_z.x.t(trp1)] + _b[_z.x.t(trp2)]</code>	<code>itsa posttrend option</code>
Difference preintervention versus first intervention: control	β_3	<code>lincom _b[_x.t(trp1)]</code>	In regression output
Difference preintervention versus first intervention: treatment	$\beta_3 + \beta_7$	<code>lincom _b[_x.t(trp1)] + _b[_z.x.t(trp1)]</code>	
Difference preintervention versus first intervention: treatment versus control	β_7	<code>lincom _b[_z.x.t(trp1)]</code>	In regression output
Difference first versus second intervention: control	β_9	<code>lincom _b[_x.t(trp2)]</code>	In regression output
Difference first versus second intervention: treatment	$\beta_9 + \beta_{11}$	<code>lincom _b[_x.t(trp2)] + _b[_z.x.t(trp2)]</code>	
Difference first versus second intervention: treatment versus control	β_{11}	<code>lincom _b[_z.x.t(trp2)]</code>	In regression output
Difference preintervention versus second intervention: control	$\beta_3 + \beta_9$	<code>lincom _b[_x.t(trp1)] + _b[_x.t(trp2)]</code>	

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Measure of interest	Model parameters	lincom specification (following <code>itssa</code>)	Notes
Difference preintervention versus second intervention: treatment	$\beta_3 + \beta_5 + \beta_7 + \beta_9 + \beta_{11}$	<code>lincom _b[_x.t(trp1)] + _b[_z.t] + _b[_z.x.t(trp1)] + _b[_x.t(trp2)] + _b[_z.x.t(trp2)]</code>	
Difference preintervention versus second intervention: treatment versus control	$\beta_5 + \beta_7 + \beta_{11}$	<code>lincom _b[_z.t] + _b[_z.x.t(trp1)] + _b[_z.x.t(trp2)]</code>	

Note: *trp* = treatment period

4 Example

To demonstrate how the measures of interest are calculated following the `itsa` command, we use the example data presented in [Linden \(2015\)](#). Briefly, in 1988, California passed the voter-initiative Proposition 99, which was a widespread effort to reduce smoking rates by raising the cigarette excise tax by 25 cents per pack and to fund antismoking campaigns and other related activities throughout the state (for a comprehensive discussion of this initiative, see [Abadie, Diamond, and Hainmueller \[2010\]](#)). The dependent variable for our analyses is the per capita cigarette sales (in packs), for the years 1970 to 2000. California's actual intervention period commenced in 1989, and we use 38 states with no such intervention in place during those years as controls.

For illustration, we derive the various measures of interest using the most complex scenario: the multiple-group, multiple-intervention analysis (2.2). In this example, we use `itsa` to assess the impact of Proposition 99 in reducing California's per capita cigarette sales (in packs), compared with that of the other 38 states in the data file. However, for exposition, we add a fictitious intervention to the cigarette sales data, starting in 1982 (in addition to the actual intervention in 1989).

First, we load the data and declare the dataset as panel:

```
. use cigsales
. tsset state year
    panel variable:  state (strongly balanced)
    time variable:  year, 1970 to 2000
                   delta: 1 unit
```

Next, we specify a multiple-group ITSA with California (state number 3 in the study) as the treatment group and, by default, all other 38 states as controls. Additionally, we specify 1982 and 1989 as the start of the interventions and request postintervention trend estimates and a figure. We fit the model using `newey` with one lag:

```
. itsa cigsale, treat(3) trperiod(1982 1989) lag(1) posttrend figure
   panel variable: state (strongly balanced)
   time variable: year, 1970 to 2000
   delta: 1 unit
```

```
Regression with Newey-West standard errors      Number of obs      =      1,209
maximum lag: 1                                F( 11,      1197) =      405.05
                                              Prob > F          =      0.0000
```

cigsale	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
_t	1.592952	.5958503	2.67	0.008	.4239245	2.761979
_z	-.6469976	4.577683	-0.14	0.888	-9.628173	8.334177
_z_t	-1.796798	.6679163	-2.69	0.007	-3.107215	-.486381
_x1982	-10.24134	5.43969	-1.88	0.060	-20.91373	.4310467
_x_t1982	-5.130358	1.195146	-4.29	0.000	-7.475172	-2.785543
_z_x1982	2.20087	6.02712	0.37	0.715	-9.624026	14.02576
_z_x_t1982	1.491346	1.243095	1.20	0.230	-.947542	3.930234
_x1989	-1.948573	4.753687	-0.41	0.682	-11.27506	7.377912
_x_t1989	2.486127	1.108565	2.24	0.025	.3111804	4.661074
_z_x1989	-7.336589	5.285895	-1.39	0.165	-17.70724	3.034061
_z_x_t1989	-1.917395	1.144526	-1.68	0.094	-4.162896	.3281052
_cons	125.6765	4.206786	29.87	0.000	117.423	133.93

Comparison of Linear Postintervention Trends: 1982

```
Treated   : _b[_t] + _b[_z_t] + _b[_x_t1982] + _b[_z_x_t1982]
Controls  : _b[_t] + _b[_x_t1982]
Difference : _b[_z_t] + _b[_z_x_t1982]
```

Linear Trend	Coef	Std. Err.	t	P> t	[95% Conf. Interval]	
Treated	-3.8429	0.2019	-19.0309	0.0000	-4.2390	-3.4467
Controls	-3.5374	0.9930	-3.5622	0.0004	-5.4857	-1.5891
Difference	-0.3055	1.0134	-0.3014	0.7631	-2.2936	1.6827

Comparison of Linear Postintervention Trends: 1989

```
Treated   : _b[_t] + _b[_z_t] + _b[_x_t1982] + _b[_z_x_t1982] + _b[_x_t1989]
> + _b[_z_x_t1989]
Controls  : _b[_t] + _b[_x_t1982] + _b[_x_t1989]
Difference : _b[_z_t] + _b[_z_x_t1982] + _b[_z_x_t1989]
```

Linear Trend	Coef	Std. Err.	t	P> t	[95% Conf. Interval]	
Treated	-3.2741	0.2521	-12.9865	0.0000	-3.7688	-2.7795
Controls	-1.0513	0.4259	-2.4686	0.0137	-1.8868	-0.2158
Difference	-2.2228	0.4949	-4.4916	0.0000	-3.1938	-1.2519

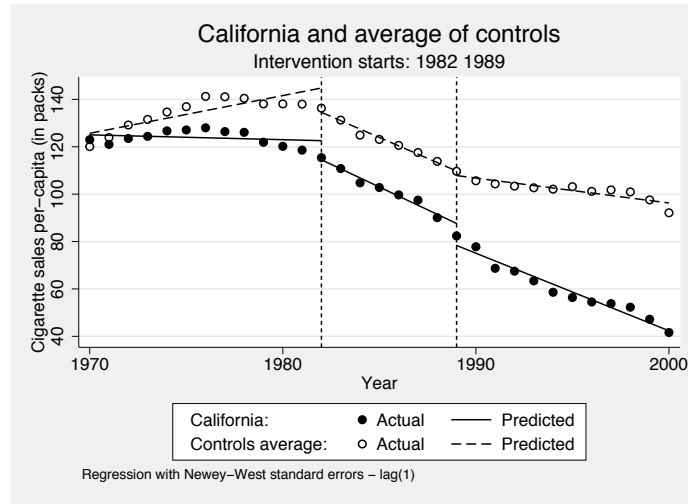


Figure 1. Multiple-group ITSA with 2 intervention periods, using Newey–West standard errors and 1 lag; all 38 “nontreated” states are used for comparison

As part of the regression output or the `posttrend` option, `itsa` provides 12 of the measures of interest. However, six important measures are not inherently calculated (see table 1). Table 2 provides a composite of all measures (both provided by `itsa` and calculated using `lincom`) following estimation of the ITSA model above.

Table 2. `lincom` estimates for all measures of interest following `itsa` estimation of a multiple-group, multiple-intervention design

Measure of interest	<code>lincom</code> specification (following <code>itsa</code>)	Point estimate [95% CI]
Preintervention trend: control	<code>lincom _b[_t]</code>	1.593 [0.424, 2.762]
Preintervention trend: treatment	<code>lincom _b[_z,t] + _b[_t]</code>	-0.204 [-0.796, 0.388]
Difference preintervention: treatment versus control	<code>lincom _b[_z,t]</code>	-1.797 [-3.107, -0.486]
First-intervention trend: control	<code>lincom _b[_t] + _b[_x,t1982]</code>	-3.537 [-5.486, -1.589]
First-intervention trend: treatment	<code>lincom _b[_t] + _b[_z,t] + _b[_x,t1982] + _b[_z,x,t1982]</code>	-3.843 [-4.239, -3.447]
Difference first intervention: treatment versus control	<code>lincom _b[_z,t] + _b[_z,x,t1982]</code>	-0.305 [-2.293, 1.683]
Second-intervention trend: control	<code>lincom _b[_t] + _b[_x,t1982] + _b[_x,t1989]</code>	-1.051 [-1.887, -0.216]
Second-intervention trend: treatment	<code>lincom _b[_t] + _b[_z,t] + _b[_x,t1982] + _b[_z,x,t1982] + _b[_x,t1989] + _b[_z,x,t1989]</code>	-3.274 [-3.769, -2.779]
Difference second intervention: treatment versus control	<code>lincom _b[_z,t] + _b[_z,x,t1982] + _b[_z,x,t1989]</code>	-2.223 [-3.194, -1.252]
Difference preintervention versus first intervention: control	<code>lincom _b[_x,t1982]</code>	-5.130 [-7.475, -2.786]
Difference preintervention versus first intervention: treatment	<code>lincom _b[_x,t1982] + _b[_z,x,t1982]</code>	-3.639 [-4.310, -2.968]
Difference preintervention versus first intervention: treatment versus control	<code>lincom _b[_z,x,t1982]</code>	1.491 [-0.947, 3.930]
Difference first versus second intervention: control	<code>lincom _b[_x,t1989]</code>	2.486 [0.311, 4.661]
Difference first versus second intervention: treatment	<code>lincom _b[_x,t1989] + _b[_z,x,t1989]</code>	0.569 [0.010, 1.127]
Difference first versus second intervention: treatment versus control	<code>lincom _b[_z,x,t1989]</code>	-1.917 [-4.163, 0.328]
Difference preintervention versus second intervention: control	<code>lincom _b[_x,t1982] + _b[_x,t1989]</code>	-2.644 [-4.081, -1.207]
Difference preintervention versus second intervention: treatment	<code>lincom _b[_z,t] + _b[_x,t1982] + _b[_z,x,t1982] + _b[_x,t1989]</code>	-4.867 [-6.137, -3.598]
Difference preintervention versus second intervention: treatment versus control	<code>lincom _b[_z,t] + _b[_z,x,t1982] + _b[_z,x,t1989]</code>	-2.223 [-3.194, -1.252]

It is helpful to visually inspect the figure to interpret the related estimates provided in table 2. For example, we see in table 2 that the preintervention trend in annual cigarette sales per capita for the control states appears to be increasing, while the preintervention trend in sales for California appears to be decreasing. Table 2 confirms this by revealing that the control states had an annual increase in cigarette sales of 1.593 (95% CI: [0.424, 2.762]) packs per capita between 1970 and 1982, while California had an annual decrease in cigarette sales of -3.390 (95% CI: $[-5.802, -0.978]$) packs per capita over the same period. The difference in trends between California and the control states for the preintervention period was thus -1.797 (95% CI: $[-3.107, -0.486]$). All other estimates are interpreted accordingly.

5 Discussion

Interrupted time-series designs offer a reasonably robust quasi-experimental approach for evaluating treatment effects when studying a single unit, the outcome variable is serially ordered as a time series, and multiple observations are captured in both the preintervention and postintervention periods. ITSA is gaining in popularity across many disciplines and was recently added as an acceptable primary research design for inclusion in systematic reviews of the literature (Cochrane Effective Practice and Organisation of Care [EPOC] Group 2015).

This article fills a gap in the current ITSA literature by providing the calculations and Stata code for a comprehensive set of measures of interest that investigators may require after ITSA estimation using the `itsa` command or after a longitudinal model when multiple treatment units are available (Linden and Adams 2010). Further, understanding how to derive measures that capture the components of ITSA may serve as a helpful framework for understanding similar components of more complex models, such as `arma`, and for exploring alternative estimation using bootstrapping techniques (Politis 2003).

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