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xtteifeci: A command for estimation and inference of treatment effects through a factor-based approach[1]

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[1] A joint work with Xingyu Li (Peking University), Yan Shen (Peking University) and Qiankun Zhou (Louisiana State University).

Outline

1 Introduction

1 Introduction

A factor-based approach to estimate treatment effects is a widely used method that leverages the advantages of panel data and factor models for causal inferences:

- proposed by Gobillon and Magnac (2016, *Review of Economics and Statistics*, 98(3): 535-551) and Xu (2017, *Political Analysis*, 25(1): 57-76)
- formalized by Bai and Ng (2021, *Journal of the American Statistical Association*, 116(536): 1746-1763)
- augmented by Li, Shen and Zhou (2024, *Journal of Econometrics*, 240(1): 105684) with easy-to-implement, nonparametric confidence intervals

1 Introduction

The xtteifeci command for Stata, designed to estimate treatment effects and provide nonparamametric confidence intervals for panel data models with interactive fixed effects as proposed by Li et al. (2024):

- report confidence intervals and p-values of treatment effects
- support statistical inference for models with diverse specifications, including those with or without covariates and/or nonstationary trends

1 Introduction

Compared with the Stata command `fect` (Liu et al. 2024), `xtteifeci` contains several distinctive features:

- provides pointwise confidence intervals and p-values of the treatment effects for each treated unit at posttreatment periods
- employs a residual-based resampling bootstrap scheme to construct confidence intervals
- estimate the unknown factor number using the method proposed by Bai and Ng (2002) or Alessi et al. (2010)
- deals with models with or without a nonstationary trend

1 Introduction

RCM and SCM also utilize factor structure to predict counterfactual outcomes and estimate the treatment effects. Compared to SCM and RCM:

- excels when multiple units are treated in the same or different periods
- applies asymptotic principal components analysis (APCA) to predict counterfactual outcomes for all treated units
- provides confidence intervals and p-values of the treatment effects

2 The model

- Factor-based Estimation of Treatment Effects
- Nonparametric Construction of Confidence Intervals

2 The model

Consider a panel data setting with $i = 1, \ldots, N$ units over $t = 1, \ldots, T$ time periods:

- assume that the policy intervention occurs in units $i = N_0 + 1, \ldots, N$ at time $t = T_0 + 1, \ldots, T$

Let y_{it}^1 and y_{it}^0 be the potential outcomes with and without intervention, the treatment effects is expressed as:

$$\Delta_{it} = y_{it}^1 - y_{it}^0$$

2 The model

The observed outcome takes the form

$$\mathscr{Y}_{i,t} = y_{it} + d_{it}\Delta_{it} \tag{1}$$

- y_{it} is the potential outcome of unit i at time t in the absence of treatment (i.e., $y_{it} = y_{it}^0$)
- d_{it} denotes the treatment variable with $d_{it} = 1$ if unit i is treated in period t and is under the treatment and $d_{it} = 0$ otherwise
- a prevalent approach is to construct counterfactual outcomes $\hat{y}_{i,t}$ as a proxy for the unobserved $y_{i,t}$ for $(i,t)|d_{it} = 1$
- construction of counterfactual outcomes relies on the data generating process of $y_{i,t}$

2 The model

For notational convenience, we categorize the observations into :

- treated set $\mathcal{I}_1 = \{(i,t)|d_{i,t} = 1\}$
- untreated set $\mathcal{I}_0 = \{(i,t)|d_{i,t} = 0\}$
- $\mathcal{I} = \mathcal{I}_0 \cup \mathcal{I}_1$

The matrix of observed outcomes $\mathscr{Y}_{i,t}$ for $(i,t) \in \mathcal{I}$ can be represented as:

$$\begin{bmatrix} y_{1,1} & \cdots & y_{N_0,1} & y_{N_0+1,1} & \cdots & y_{N,1} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ y_{1,T_0} & \cdots & y_{N_0,T_0} & y_{N_0+1,T_0} & \cdots & y_{N,T_0} \\ y_{1,T_0+1} & \cdots & y_{N_0,T_0+1} & y_{N_0+1,T_0+1} + \Delta_{N_0+1,T_0+1} & \cdots & y_{N,T_0+1} + \Delta_{N,T_0+1} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ y_{1,T} & \cdots & y_{N_0,T} & y_{N_0+1,T} + \Delta_{N_0+1,T} & \cdots & y_{N,T} + \Delta_{N,T} \end{bmatrix}$$

2 The model

Assume that $y_{i,t}$ are generated by an pure factor model

$$y_{i,t} = c_{i,t} + e_{i,t} = \mathbf{f}_t^{\top} \boldsymbol{\lambda}_i + e_{i,t} \tag{2}$$

- $\mathbf{f}_t$ is an $(r \times 1)$ vector of unobserved common factor
- $\boldsymbol{\lambda}_i$ is an $(r \times 1)$ vector of unobserved factor loading
- $c_{i,t} = \mathbf{f}_t^{\top} \boldsymbol{\lambda}_i$ is the common component
- $e_{i,t}$ is the idiosyncratic error term

Our objective is to obtain the prediction of counterfactual outcomes $\hat{y}_{i,t}$ based on Equation (2), and estimate the treatment effects.

2 The model

$$
\begin{bmatrix}
y_{1,1} & \cdots & y_{N_0,1} & y_{N_0+1,1} & \cdots & y_{N,1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
y_{1,T_0} & \cdots & y_{N_0,T_0} & y_{N_0+1,T_0} & \cdots & y_{N,T_0} \\
y_{1,T_0+1} & \cdots & y_{N_0,T_0+1} & y_{N_0+1,T_0+1}+\Delta_{N_0+1,T_0+1} & \cdots & y_{N,T_0+1}+\Delta_{N,T_0+1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
y_{1,T} & \cdots & y_{N_0,T} & y_{N_0+1,T}+\Delta_{N_0+1,T} & \cdots & y_{N,T}+\Delta_{N,T}
\end{bmatrix}
$$

$$
\mathbf{Y}_{\text{wide}} = \begin{bmatrix}
y_{1,1} & \cdots & y_{N_0,1} & y_{N_0+1,1} & \cdots & y_{N,1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
y_{1,T_0} & \cdots & y_{N_0,T_0} & y_{N_0+1,T_0} & \cdots & y_{N,T_0}
\end{bmatrix}
\quad
\mathbf{Y}_{\text{tall}} = \begin{bmatrix}
y_{1,1} & \cdots & y_{N_0,1} \\
\vdots & \ddots & \vdots \\
y_{1,T_0} & \cdots & y_{N_0,T_0} \\
y_{1,T_0+1} & \cdots & y_{N_0,T_0+1} \\
\vdots & \ddots & \vdots \\
y_{1,T} & \cdots & y_{N_0,T}
\end{bmatrix}
$$

2.1 Factor-based Estimation of Treatment Effects

Define $\mathbf{y}_i = (y_{i,1}, \ldots, y_{i,T})^\top$, $\mathbf{Y} = (\mathbf{y}_1, \ldots, \mathbf{y}_N)$, $\mathbf{F} = (\mathbf{f}_1, \ldots, \mathbf{f}_T)^\top$ and $\boldsymbol{\Lambda} = (\boldsymbol{\lambda}_1, \ldots, \boldsymbol{\lambda}_N)^\top$.

- The tall block of $\mathbf{Y}$, denoted as $\mathbf{Y}_{\text{tall}}$, corresponds to the submatrix of $\mathbf{Y}$ across untreated units
- The wide block of $\mathbf{Y}$, denoted as $\mathbf{Y}_{\text{wide}}$, corresponds to the submatrix of $\mathbf{Y}$ during the pretreatment periods

Let $(\mathbf{F}_{\text{tall}}, \boldsymbol{\Lambda}_{\text{tall}})$ and $(\mathbf{F}_{\text{wide}}, \boldsymbol{\Lambda}_{\text{wide}})$ be the common factor and factor loading matrices associated with $\mathbf{Y}_{\text{tall}}$ and $\mathbf{Y}_{\text{wide}}$, respectively:

- $\mathbf{F}_{\text{tall}} = \mathbf{F}$ and $\boldsymbol{\Lambda}_{\text{wide}} = \boldsymbol{\Lambda}$

2.1 Factor-based Estimation of Treatment Effects

Given that $\mathbf{Y}_{\text{tall}}$ spans all times, we apply asymptotic principal component analysis (APCA) to $\mathbf{Y}_{\text{tall}}$ to estimate common factors for all periods:

- conduct singular value decomposition (SVD) on $\mathbf{Y}_{\text{tall}}/\sqrt{TN_0}$ to obtain $\mathbf{D}_{\text{tall}}$, $\mathbf{P}_{\text{tall}}$ and $\mathbf{Q}_{\text{tall}}$
- estimate the common factor matrix associated with $\mathbf{Y}_{\text{tall}}$ as

$$\hat{\mathbf{F}}_{\text{tall}} = \left(\hat{\mathbf{f}}_{\text{tall},1}, \ldots, \hat{\mathbf{f}}_{\text{tall},T}\right)^{\mathsf{T}} = \sqrt{T}\mathbf{P}_{\text{tall}}$$

- estimate the factor loading matrix associated with $\mathbf{Y}_{\text{tall}}$ as

$$\hat{\mathbf{\Lambda}}_{\text{tall}} = \left(\hat{\boldsymbol{\lambda}}_{\text{tall},1}, \ldots, \hat{\boldsymbol{\lambda}}_{\text{tall},N_0}\right)^{\mathsf{T}} = \sqrt{N_0}\mathbf{Q}_{\text{tall}}\mathbf{D}_{\text{tall}} \tag{3}$$

2.1 Factor-based Estimation of Treatment Effects

Similarly, given that $\mathbf{Y}_{\text{wide}}$ contains all units, we apply APCA to $\mathbf{Y}_{\text{wide}}$ to estimate the factor loadings for all units:

- conduct SVD on $\mathbf{Y}_{\text{wide}}/\sqrt{T_0 N}$ to obtain $\mathbf{D}_{\text{wide}}$, $\mathbf{P}_{\text{wide}}$ and $\mathbf{Q}_{\text{wide}}$
- estimate the common factor matrix associated with $\mathbf{Y}_{\text{wide}}$ as

$$\hat{\mathbf{F}}_{\text{wide}} = \left(\hat{\mathbf{f}}_{\text{wide},1}, \ldots, \hat{\mathbf{f}}_{\text{wide},T_0}\right)^{\mathsf{T}} = \sqrt{T_0}\mathbf{P}_{\text{wide}}$$

- estimate the factor loading matrix associated with $\mathbf{Y}_{\text{wide}}$ as

$$\hat{\boldsymbol{\Lambda}}_{\text{wide}} = \left(\hat{\boldsymbol{\lambda}}_{\text{wide},1}, \ldots, \hat{\boldsymbol{\lambda}}_{\text{wide},N}\right)^{\mathsf{T}} = \sqrt{N}\mathbf{Q}_{\text{wide}}\mathbf{D}_{\text{wide}} \tag{4}$$

2.1 Factor-based Estimation of Treatment Effects

Compute a rotation matrix as

$$\hat{\mathbf{H}}_{\text{miss}} = \hat{\mathbf{\Lambda}}_{\text{tall}}^{\mathsf{T}} \hat{\mathbf{\Lambda}}_{\text{wide},0} \left(\hat{\mathbf{\Lambda}}_{\text{wide},0}^{\mathsf{T}} \hat{\mathbf{\Lambda}}_{\text{wide},0} \right)^{-1} .$$

- $\hat{\mathbf{\Lambda}}_{\text{wide},0}$ is the submatrix of $\hat{\mathbf{\Lambda}}_{\text{wide}}$ corresponding to the untreated units

The common component for unit i at time t is estimated by

$$\hat{c}_{i,t} = \hat{\boldsymbol{\lambda}}_{\text{wide},i}^{\mathsf{T}} \hat{\mathbf{H}}_{\text{miss}} \hat{\mathbf{f}}_{\text{tall},t}$$

The predicted counterfactual outcomes $\hat{y}_{i,t} = \hat{c}_{i,t}$.

2.1 Factor-based Estimation of Treatment Effects

The residual is computed as

$$\hat{e}_{i,t} = \mathscr{Y}_{i,t} - \hat{c}_{i,t},$$

The estimated treatment effect $\hat{\Delta}_{i,t} = \hat{e}_{i,t}$ for $(i,t) \in \mathcal{I}_1$.

The standard error of $\hat{\Delta}_{i,t}$ is given by

$$\mathrm{se}(\hat{\Delta}_{i,t}) = \sqrt{\hat{v}_{i,t} + \hat{\sigma}_i^2} \tag{5}$$

- $\hat{v}_{i,t}$ is the variance of $\hat{c}_{i,t}$
- $\hat{\sigma}_i^2 = \frac{1}{T_0} \sum_{s=1}^{T_0} \hat{e}_{i,s}^2$

2.2 Nonparametric Construction of Confidence Intervals

Construct confidence intervals of treatment effects using the scheme suggested by Li et al. (2024). Recall that $\mathscr{Y}_{i,t} = c_{i,t} + e_{i,t} + \Delta_{i,t}$, $\hat{y}_{i,t} = \hat{c}_{i,t}$, and $\hat{\Delta}_{i,t} = \mathscr{Y}_{i,t} - \hat{y}_{i,t}$:

$$\Delta_{i,t} - \hat{\Delta}_{i,t} = \hat{c}_{i,t} - c_{i,t} - e_{i,t} = \hat{c}_{i,t} - y_{i,t}. \tag{6}$$

The standardized difference between the true and estimated treatment effects, $(\Delta_{i,t} - \hat{\Delta}_{i,t})/\mathrm{se}(\hat{\Delta}_{i,t})$, can be rewritten as

$$s_{i,t} = \frac{\hat{c}_{i,t} - y_{i,t}}{\sqrt{\hat{v}_{i,t} + \hat{\sigma}_i^2}}.$$

2.2 Nonparametric Construction of Confidence Intervals

Adopt a residual-based resampling scheme to construct the empirical distribution of $s_{i,t}$ as follow:

1. For $(i,t) \in \mathcal{I}_0$, draw the bootstrap idiosyncratic error $e^*_{i,t}$ by $e^*_{i,t} = u_{T,t}\hat{e}_{i,t}$
   - $\{u_{T,t} : t = 1, \ldots, T\}$ is the random multipliers
2. For $(i,t) \in \mathcal{I}_1$, draw the bootstrap idiosyncratic error $e^*_{i,t}$ from the empirical distribution $\{\hat{e}_{i,s} : s = 1, \ldots, T_0\}$.
3. For $(i,t) \in \mathcal{I}$, construct the bootstrap outcomes $y^*_{i,t}$ by $y^*_{i,t} = \hat{c}_{i,t} + e^*_{i,t}$.
4. Apply the factor-based estimation procedure to $\mathbf{Y}^*$

$$s^*_{i,t}(b) = \frac{\hat{c}^*_{i,t} - y^*_{i,t}}{\sqrt{\hat{v}^*_{i,t} + (\hat{\sigma}^*_i)^2}}.$$

2.2 Nonparametric Construction of Confidence Intervals

Execute the previous resampling scheme B times to obtain B statistics denoted by $s^*_{i,t}(1), \ldots, s^*_{i,t}(B)$.

- let $q_{\alpha/2,i,t}$ and $q_{1-\alpha/2,i,t}$ be $\alpha/2$ and $(1-\alpha/2)$ empirical quantile of $\left\{s^*_{i,t}(1), \ldots, s^*_{i,t}(B)\right\}$
- let $p_{1-\alpha,i,t}$ be $(1-\alpha)$ empirical quantile of $\left\{\left|s^*_{i,t}(1)\right|, \ldots, \left|s^*_{i,t}(B)\right|\right\}$

2.2 Nonparametric Construction of Confidence Intervals

The equal tailed $(1-\alpha)$ confidence interval is estimated by

$$\mathrm{EQ}_{1-\alpha,i,t} = \left[\hat{\Delta}_{i,t} + q_{\alpha/2,i,t}\sqrt{\hat{v}_{i,t} + \hat{\sigma}_i^2},\ \hat{\Delta}_{i,t} + q_{1-(\alpha/2),i,t}\sqrt{\hat{v}_{i,t} + \hat{\sigma}_i^2}\right]$$

The symmetric $(1-\alpha)$ confidence interval is estimated by

$$\mathrm{SY}_{1-\alpha,i,t} = \left[\hat{\Delta}_{i,t} - p_{1-\alpha,i,t}\sqrt{\hat{v}_{i,t} + \hat{\sigma}_i^2},\ \hat{\Delta}_{i,t} + p_{1-\alpha,i,t}\sqrt{\hat{v}_{i,t} + \hat{\sigma}_i^2}\right]$$

2.2 Nonparametric Construction of Confidence Intervals

For the null hypothesis $H_0 : \Delta_{i,t} = 0$:

- p-value based on the equal-tailed empirical distribution of $\Delta_{i,t}$:

$$p_{i,t}^{\mathrm{EQ}} = 2\min\left\{\frac{1}{B}\sum_{b=1}^{B}\mathbf{1}\left(s_{i,t}^{*}(b) \geq s_{i,t}\right), \frac{1}{B}\sum_{b=1}^{B}\mathbf{1}\left(s_{i,t}^{*}(b) \leq s_{i,t}\right)\right\},$$

- p-value based on the symmetric empirical distribution of $\Delta_{i,t}$:

$$p_{i,t}^{\mathrm{SY}} = \frac{1}{B}\sum_{b=1}^{B}\mathbf{1}\left(\left|s_{i,t}^{*}(b)\right| \geq \left|s_{i,t}\right|\right).$$

For the panel data with small size ($T_0 \leq 50$ and $N_0 \leq 50$), $p_{i,t}^{\mathrm{EQ}}$ is generally recommended

3 Extensions

- The model with covariates
- The model with nonstationary trend

3.1 The model with covariates

Assume that the untreated potential outcomes $y_{i,t}$ are influenced by both exogenous covariates and interactive fixed effects of the form

$$y_{i,t} = \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta} + c_{i,t} + e_{i,t} = \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta} + \mathbf{f}_t^{\top}\boldsymbol{\lambda_i} + e_{i,t} \tag{7}$$

- $\mathbf{x}_{i,t}$ is a $(p \times 1)$ vector of the covariates
- $\boldsymbol{\beta}$ is a $(p \times 1)$ vector of coefficients
- We employ the interactive fixed effect estimation (IFEE) proposed by Bai (2009) instead of APCA to estimate the coefficients $\boldsymbol{\beta}$ and the common components $c_{i,t}$ simultaneously

3.2 The model with nonstationary trend

Assume that all untreated potential outcomes $y_{i,t}$ are generated by a pure factor model as in Equation (2), and the common factors $\mathbf{f}_t$ follow a vector-valued integrated process of the form

$$\mathbf{f}_t = \mathbf{f}_{t-1} + \boldsymbol{\eta}_t \tag{8}$$

- $\boldsymbol{\eta}_t$ is an $(r \times 1)$ vector of zero-mean weakly stationary process driving the stochastic trends

To accommodate integrated common factors, we apply the modified APCA instead of APCA described in Section 2.1

3.2 The model with nonstationary trend

Assume the untreated potential outcomes $y_{i,t}$ are generated by Equation (7), the common factors $\mathbf{f}_t$ follow Equation (8), and the covariates $\mathbf{x}_{i,t}$ are generated by another vector-valued integrated process:

$$\mathbf{x}_{i,t} = \mathbf{x}_{i,t-1} + \boldsymbol{\varepsilon}_{i,t},$$

- $\boldsymbol{\varepsilon}_{i,t}$ is a $(p \times 1)$ vector of weakly stationary processes

To estimate the common stochastic trends, factor loadings, and coefficients on covariates, we utilize the continuously-updated (Cup) estimation proposed by Bai (2009) instead of the IFEE described in Section 3.1.

4 The xtteifeci command

- Syntax

4 The xtteifeci command

The syntax for `xtteifeci` is

`xtteifeci` *depvar* [*indepvars*] , `treatvar(`*treatvarname*`)` [`r(#)`
`iterate(#)` `tolerance(`*real*`)` `trend({0|1})` `bootstrap(#)` `seed(`*int*`)`
`rmethod({bn|abc})` `rmax(#)` `citype({eq|sy})` `frame(`*framename*`)`
`nofigure` `savegraph(`*prefix* [, `asis` `replace`]`)`]

- `xtset` *panelvar* *timevar* must be used to declare a balanced panel dataset in the usual long form; see [XT] **xtset**
- *depvar* and *indepvars* must be numeric variables, and abbreviations are not allowed

5 Examples

- Example 1: Political and economic integration between Hong Kong and Chinese mainland
- Example 2: California tobacco control programme

5 Examples

To begin with, the Stata command `xtteifeci` can be installed from the SSC (Stata version >= 17):

```
. ssc install xtteifeci, all replace
```

- "`all`" specifies downloading two example datasets ("`growth2.dta`" and "`smoking2.dta`") attached to the `xtteifeci` command
- "`replace`" instructs replacement of previous version of the `xtteifeci` command if installed.

5.1 Integration between HK and Chinese mainland

The case in Hsiao et al. (2012): evaluates the effects of political and economic integration between Hong Kong and Chinese mainland on the economy of Hong Kong.

[2] Image source: https://www.sohu.com/a/800519984_121136655.

The panel dataset `growth2.dta` attached to the `xtteifeci` command includes the following variables across Hong Kong and other 24 countries or regions from 1993Q1 to 2008Q1:

- the outcome variable `gdp` representing quarterly real GDP growth rates
- the treatment variable `pi` indicating political integration
- the treatment variable `ei` indicating economic integration

5.1 Integration between HK and Chinese mainland

```
. use growth2, clear

. xtset region time

Panel variable: region (strongly balanced)
 Time variable: time, 1993q1 to 2008q1
         Delta: 1 quarter

. panelview gdp pi, i(region) t(time) type(treat)

   #  Variable        # Missing   % Missing
--------------------------------------------
   1  gdp                     0         0.0
   2  pi                   1041        68.3
```

(*output omitted*)

5.1 Integration between HK and Chinese mainland

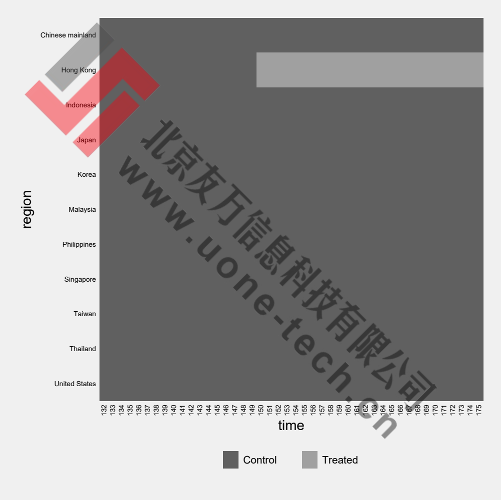


Figure 1: Treatment status of political integration

5.1 Integration between HK and Chinese mainland

```
. xtteifeci gdp if !missing(pi), treatvar(pi)

Estimation results based on the data from control units and the pre-treatment d
> ata of treated units:
-------------------------------------------------------------------------------
 Factor dimension   =            8     Number of Covariates      =          0
 Size of Tall Block =      (10, 44)    Number of Control Obs.    =        458
 Size of Wide Block =      (11, 18)    Mean Squared Error        =      0.000
 R-squared          =       0.91805    Root Mean Squared Error   =      0.015
-------------------------------------------------------------------------------
Note: The number of factors is estimated using the method proposed by Bai and
      Ng (2002) with the maximum number of factors set to be 8.
```

5.1 Integration between HK and Chinese mainland

Estimation and prediction results during the posttreatment periods in Hong Kong
> , with equal-tailed confidence intervals:

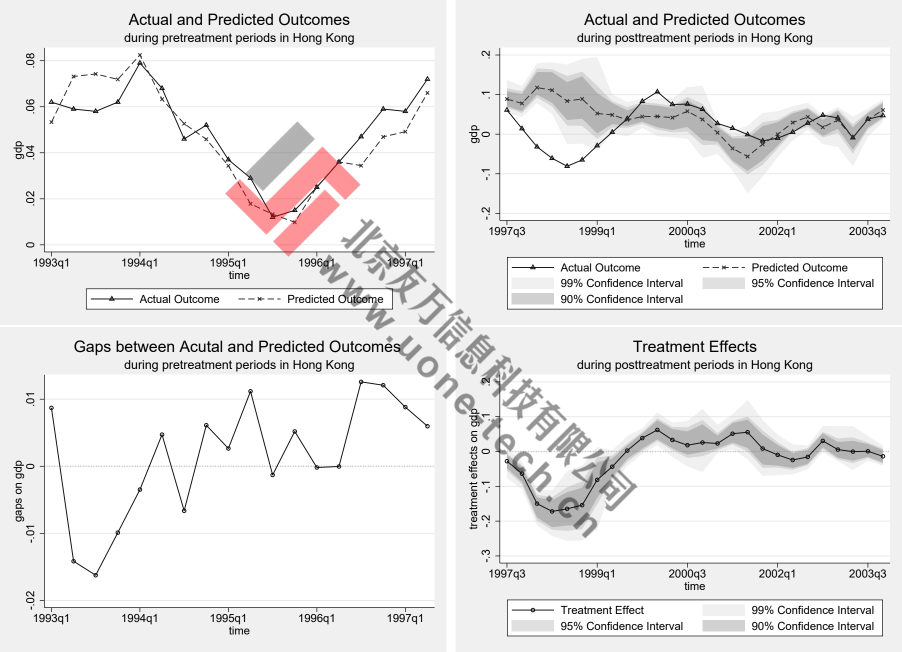
Time	Actual Outcome	Predicted Outcome	[95% Confidence	Interval]
1997q3	0.0610	0.0887	0.0670	0.1156
1997q4	0.0140	0.0777	0.0531	0.1086
1998q1	-0.0320	0.1177	0.0925	0.1663
1998q2	-0.0610	0.1111	0.0700	0.1639
1998q3	-0.0810	0.0837	0.0216	0.1468
1998q4	-0.0650	0.0890	0.0210	0.1581
(*output omitted*)				
2002q3	0.0280	0.0435	0.0180	0.0671
2002q4	0.0480	0.0175	-0.0084	0.0419
2003q1	0.0410	0.0354	0.0033	0.0632
2003q2	-0.0090	-0.0087	-0.0498	0.0249
2003q3	0.0380	0.0373	0.0122	0.0568
2003q4	0.0470	0.0608	0.0387	0.0824

5.1 Integration between HK and Chinese mainland

Time	Treatment Effect	p-value	[95% Confidence	Interval]
1997q3	-0.0277**	0.024	-0.0546	-0.0060
1997q4	-0.0637***	0.000	-0.0946	-0.0391
1998q1	-0.1497***	0.000	-0.1983	-0.1245
1998q2	-0.1721***	0.000	-0.2249	-0.1310
1998q3	-0.1647***	0.004	-0.2278	-0.1026
(*output omitted*)				
2002q4	0.0305**	0.012	0.0061	0.0564
2003q1	0.0056	0.752	-0.0222	0.0377
2003q2	-0.0003	0.872	-0.0339	0.0408
2003q3	0.0007	0.880	-0.0188	0.0258
2003q4	-0.0138	0.184	-0.0354	0.0083
Mean	-0.0217			

Note: (1) The average treatment effect over the posttreatment period is
-0.0217.
(2) ***, **, and * denote statistical significance of treatment effect
at the 1, 5, and 10 level, respectively.

Finished.


Actual and Predicted Outcomes
during pretreatment periods in Hong Kong
gdp
0
.02
.04
.06
.08
1993q1
1994q1
1995q1
1996q1
1997q1
time
Actual Outcome
Predicted Outcome
Actual and Predicted Outcomes
during posttreatment periods in Hong Kong
gdp
-.2
-.1
0
.1
.2
1997q3
1999q1
2000q3
2002q1
2003q3
time
Actual Outcome
Predicted Outcome
99% Confidence Interval
95% Confidence Interval
90% Confidence Interval
Gaps between Acutal and Predicted Outcomes
during pretreatment periods in Hong Kong
gaps on gdp
-.02
-.01
0
.01
1993q1
1994q1
1995q1
1996q1
1997q1
time
Treatment Effects
during posttreatment periods in Hong Kong
treatment effects on gdp
-.3
-.2
-.1
0
.1
.2
1997q3
1999q1
2000q3
2002q1
2003q3
time
Treatment Effect
99% Confidence Interval
95% Confidence Interval
90% Confidence Interval

5.1 Integration between HK and Chinese mainland

Consider the case of economic integration between Hong Kong and the Chinese mainland:

```
. panelview gdp ei, i(region) t(time) type(treat)

   #  Variable        # Missing   % Missing
--------------------------------------------
   1  gdp                     0         0.0
   2  ei                      0         0.0

Missing for |
   how many |
 variables? |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |      1,525      100.00      100.00
------------+-----------------------------------
      Total |      1,525      100.00
Note: White cells represent missing values/observations in data.
```

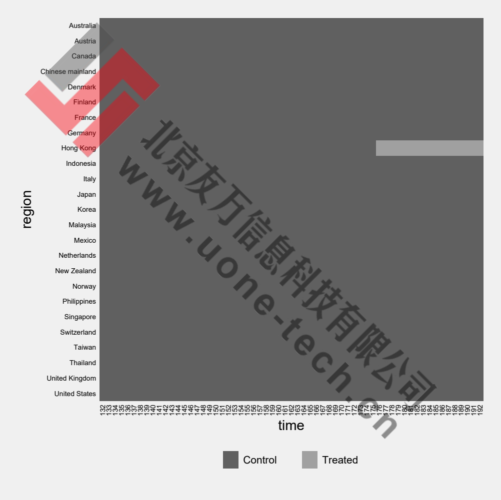


Figure 3: Treatment status of economic integration

5.1 Integration between HK and Chinese mainland

```
. xtteifeci gdp, treatvar(ei) frame(growth_ei)

Estimation results based on the data from control units and the pre-treatment d
> ata of treated units:
---------------------------------------------------------------------------------
 Factor dimension   =            8     Number of Covariates      =          0
 Size of Tall Block =     (24, 61)     Number of Control Obs.    =       1508
 Size of Wide Block =     (25, 44)     Mean Squared Error        =      0.000
 R-squared          =      0.91831     Root Mean Squared Error   =      0.011
---------------------------------------------------------------------------------
Note: The number of factors is estimated using the method proposed by Bai and
      Ng (2002) with the maximum number of factors set to be 8.
```

5.1 Integration between HK and Chinese mainland

```
Estimation and prediction results during the posttreatment periods in Hong Kong
> , with equal-tailed confidence intervals:
```

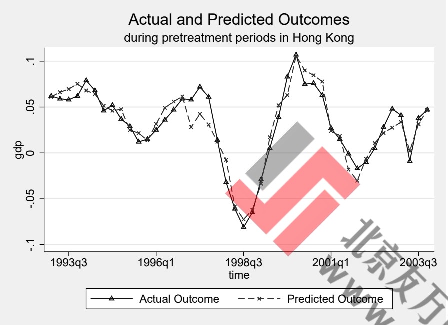
Time	Actual Outcome	Predicted Outcome	[95% Confidence	Interval]
2004q1	0.0770	0.0490	0.0213	0.0853
2004q2	0.1200	0.0741	0.0440	0.1109
2004q3	0.0660	0.0595	0.0288	0.0990
2004q4	0.0790	0.0625	0.0311	0.0992
(*output omitted*)				
2005q4	0.0690	0.0521	0.0193	0.0899
2006q1	0.0900	0.0662	0.0293	0.1126
2006q2	0.0620	0.0459	0.0094	0.0857
2006q3	0.0640	0.0376	0.0073	0.0779
2006q4	0.0660	0.0255	0.0021	0.0622
2007q1	0.0550	0.0207	-0.0036	0.0611
2007q2	0.0620	0.0408	0.0163	0.0832
2007q3	0.0680	0.0433	0.0165	0.0823
2007q4	0.0690	0.0596	0.0277	0.0984
2008q1	0.0730	0.0607	0.0271	0.1031

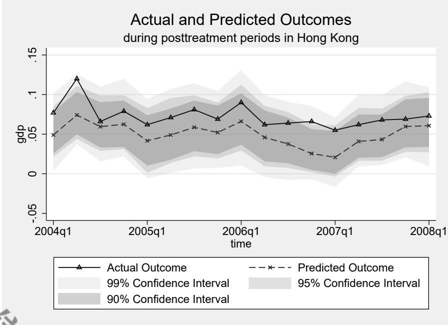
5.1 Integration between HK and Chinese mainland

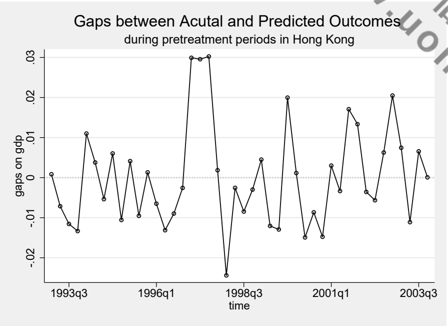
Time	Treatment Effect	*p*-value	[95% Confidence	Interval]
2004q1	0.0280	0.116	-0.0083	0.0557
2004q2	0.0459**	0.016	0.0091	0.0760
2004q3	0.0065	0.540	-0.0330	0.0372
2004q4	0.0165	0.248	-0.0202	0.0479
(*output omitted*)				
2006q4	0.0405**	0.032	0.0038	0.0639
2007q1	0.0343*	0.092	-0.0061	0.0586
2007q2	0.0212	0.260	-0.0212	0.0457
2007q3	0.0247	0.232	-0.0143	0.0515
2007q4	0.0094	0.480	-0.0294	0.0413
2008q1	0.0123	0.424	-0.0301	0.0459
Mean	0.0228			

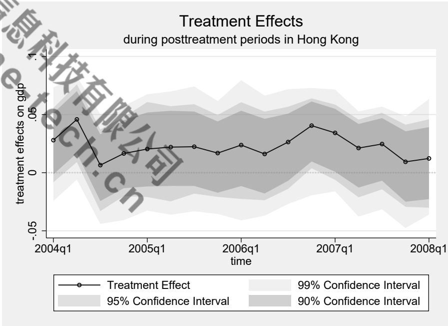
Note: (1) The average treatment effect over the posttreatment period is 0.0228.
(2) ***, **, and * denote statistical significance of treatment effect at the 1, 5, and 10 level, respectively.

Finished.


Actual and Predicted Outcomes
during pretreatment periods in Hong Kong
gdp
.1
.05
0
-.05
-.1
1993q3
1996q1
1998q3
2001q1
2003q3
time
Actual Outcome
Predicted Outcome


Actual and Predicted Outcomes
during posttreatment periods in Hong Kong
gdp
.15
.1
.05
0
-.05
2004q1
2005q1
2006q1
2007q1
2008q1
time
Actual Outcome
Predicted Outcome
99% Confidence Interval
95% Confidence Interval
90% Confidence Interval


Gaps between Acutal and Predicted Outcomes
during pretreatment periods in Hong Kong
gaps on gdp
.03
.02
.01
0
-.01
-.02
1993q3
1996q1
1998q3
2001q1
2003q3
time


Treatment Effects
during posttreatment periods in Hong Kong
treatment effects on gdp
.1
.05
0
-.05
2004q1
2005q1
2006q1
2007q1
2008q1
time
Treatment Effect
99% Confidence Interval
95% Confidence Interval
90% Confidence Interval

5.1 Integration between HK and Chinese mainland

To access the generated frame `growth2_ei`, we the following command:

```
. frame change growth_ei
. describe, simple
region          pred · gdp_q05    pred · gd_y975    tr · gdp · eq975    tr · gdp · sy005
time            pred · gd_q975    pred · gd_y025    tr · gdp · eq005    tr · gdp · sy995
gdp             pred · gd_q025    pred · gd_y995    tr · gdp · eq995    tr · gdp · eqp_l
ei              pred · gd_q995    pred · gd_y005    tr · gdp · sy05     tr · gdp · syp_l
pred · gdp       pred · gd_q005    tr · gdp · eq05    tr · gdp · sy95
tr · gdp         pred · gdp_y95    tr · gdp · eq95    tr · gdp · sy025
pred · gdp_q95   pred · gdp_y05    tr · gdp · eq025   tr · gdp · sy975
```

To illustrate the utility of this frame, we create a customized graph to visualize the treatment effects with 95% confidence intervals:

```
. twoway (rcap tr · gdp · eq025 tr · gdp · eq975 time) ///
>         (connected tr · gdp time,  msymbol(smcircle_hollow)) ///
>         if region == 9 & ei== 1, name(eff_post, replace) ///
>         legend(order(2 "Treatment Effect" 1 "95% Confidence Interval")) ///
>         ytitle("treatment effects on gdp")
```

5.1 Integration between HK and Chinese mainland

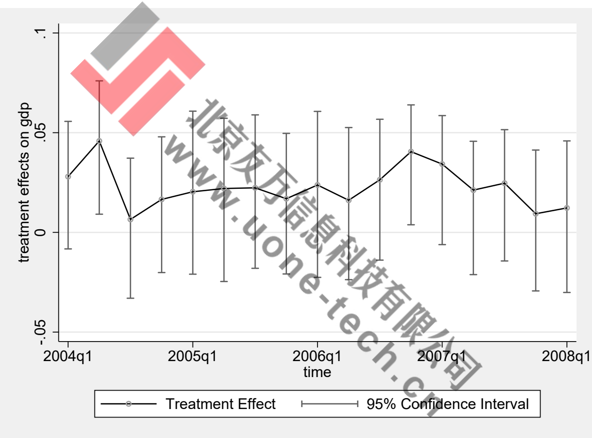


Figure 5: Treatment effects during posttreatment periods

5.2 California tobacco control programme

The case in Abadie et al. (2010): evaluates the effects of California Tobacco Control Programme (CTCP) on per capita cigarettes consumption in California.

[3] Image source: https://www.lagrantcommunications.com/ctcp.

5.2 California tobacco control programme

The dataset `smoking2.dta`, which is attached to the `xtteifeci` command and constructed by Hsiao and Zhou (2019) for reevaluating the impact of CTCP, contains the following variables for 39 U.S. states from 1970 to 2000 :

- the outcome variable `cigsale` (cigarette sales per capita in packs)
- the covariate `lnincome`, `eduattain`, `eduattain` and `poverty`
- the treatment variable `ctcp` (indicator of CTCP)

5.2 California tobacco control programme

```
. use smoking2, clear

. xtset state year

Panel variable: state (strongly balanced)
 Time variable: year, 1970 to 2000
         Delta: 1 unit

. panelview cigsale ctcp, i(state) t(year) type(treat)

   #  Variable        # Missing   % Missing
--------------------------------------------
   1  cigsale                 0         0.0
   2  ctcp                    0         0.0

Missing for |
   how many |
 variables? |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |      1,209      100.00      100.00
------------+-----------------------------------
      Total |      1,209      100.00
Note: White cells represent missing values/observations in data.
```

5.2 California tobacco control programme

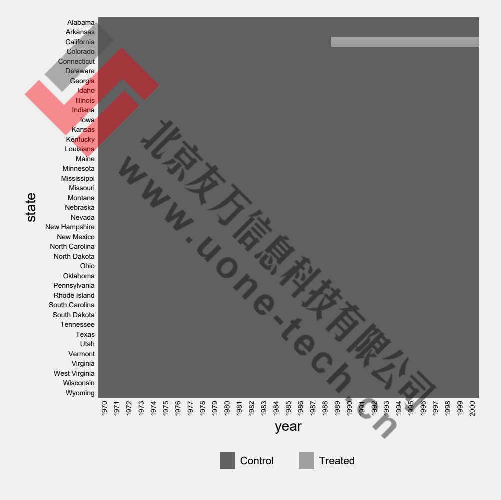


Figure 6: Treatment status of CTCP

5.2 California tobacco control programme

```
. collect clear

. foreach var of varlist cigsale lnincome eduattain poverty{
  2. collect, tags(var["`var´_tall"]): qui xtunitroot llc `var´ if state != 3
  3. collect, tags(var["`var´_wide"]): qui xtunitroot llc `var´ if year <= 1988
  4. }

. collect style row split, position(right)

. collect style cell, nformat(%9.4f) halign(right) font(bold)

. collect style column, extraspace(2)

. collect label values result tds "t statistic", modify

. collect label values result p_tds "p-value", modify
```

5.2 California tobacco control programme

```
. collect layout (var) (result[tds p_tds])

Collection: default
      Rows: var
   Columns: result[tds p_tds]
   Table 1: 8 x 2
```

	t statistic	p-value
cigsale_tall	6.9344	1.0000
cigsale_wide	4.9777	1.0000
lnincome_tall	-21.1273	0.0000
lnincome_wide	-12.6212	0.0000
eduattain_tall	-0.9866	0.1619
eduattain_wide	-5.0602	0.0000
poverty_tall	-6.0223	0.0000
poverty_wide	-6.9973	0.0000

5.2 California tobacco control programme

```
. xtteifeci cigsale lnincome eduattain poverty, treatvar(ctcp) trend(1) rmethod
> (abc)

Estimation results based on the data from control units and the pre-treatment d
> ata of treated units:
------------------------------------------------------------------------------

 Factor dimension    =             1  Number of Covariates      =          3
 Size of Tall Block =      (38, 31)  Number of Control Obs.    =       1197
 Size of Wide Block =      (39, 19)  Mean Squared Error        =    145.163
 R-squared           =       0.86142  Root Mean Squared Error   =     12.048
------------------------------------------------------------------------------

------------------------------------------------------------------------------
     cigsale | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
    lnincome |   41.82516    4.74327     8.82   0.000     32.51833    51.13199
   eduattain |  -2.553667   .1742708   -14.65   0.000    -2.895606   -2.211728
     poverty |   -.290102   .1527914    -1.90   0.058     -.589896    .0096919
       _cons |  -332.3309   51.89091    -6.40   0.000    -434.1468   -230.5151
------------------------------------------------------------------------------

Note: The number of factors is estimated using the method proposed by Alessi
      et al. (2010) with the maximum number of factors set to be 8.
```

5.2 California tobacco control programme

Estimation and prediction results during the posttreatment periods in Californi
> a, with equal-tailed confidence intervals:

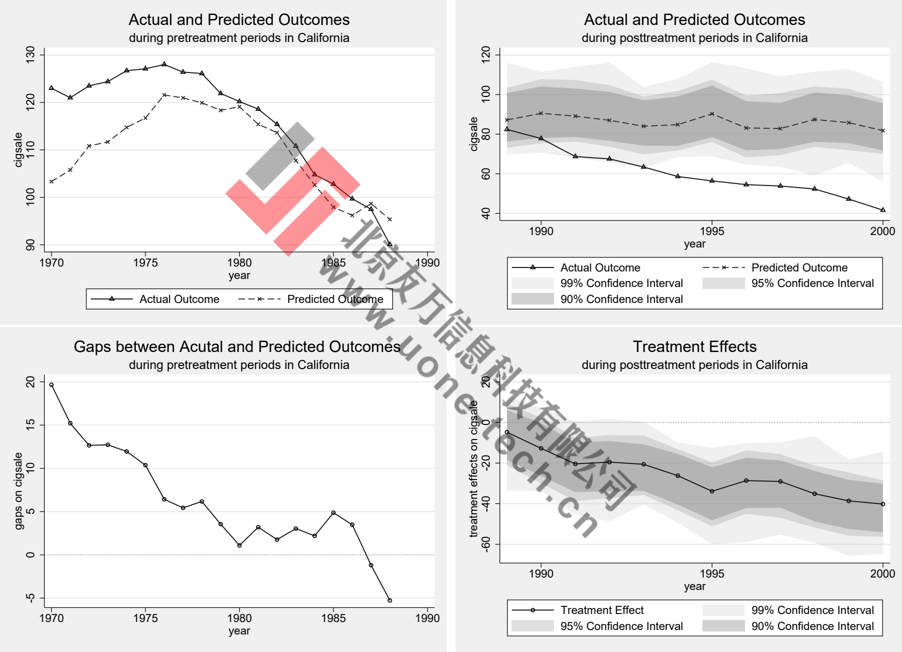
Time	Actual Outcome	Predicted Outcome	[95% Confidence	Interval]
1989	82.4000	87.1855	73.1565	103.4151
1990	77.8000	90.5470	75.4083	107.7937
1991	68.7000	89.1072	76.2704	107.3637
1992	67.5000	87.0044	73.6684	104.7835
1993	63.4000	84.0022	69.8004	99.0764
1994	58.6000	84.8180	71.7348	101.8053
1995	56.4000	90.2783	76.0631	107.5854
1996	54.5000	83.1358	68.2250	99.5033
1997	53.8000	82.8551	69.3973	100.7451
1998	52.3000	87.4098	73.5244	104.1373
1999	47.2000	85.8132	71.8777	102.9401
2000	41.6000	81.7831	70.0416	97.9608

5.2 California tobacco control programme

Time	Treatment Effect	*p*-value	[95% Confidence	Interval]
1989	-4.7855	0.452	-21.0151	9.2435
1990	-12.7470	0.100	-29.9937	2.3917
1991	-20.4072**	0.012	-38.6637	-7.5704
1992	-19.5044**	0.012	-37.2835	-6.1684
1993	-20.6022**	0.012	-35.6764	-6.4004
1994	-26.2180***	0.004	-43.2053	-13.1348
1995	-33.8783***	0.000	-51.1854	-19.6631
1996	-28.6358***	0.000	-45.0033	-13.7250
1997	-29.0551***	0.000	-46.9451	-15.5973
1998	-35.1098***	0.000	-51.8373	-21.2244
1999	-38.6132***	0.000	-55.7401	-24.6777
2000	-40.1831***	0.004	-56.3608	-28.4416
Mean	-25.8116			

Note: (1) The average treatment effect over the posttreatment period is -25.8116.
(2) ***, **, and * denote statistical significance of treatment effect at the 1, 5, and 10 level, respectively.

Finished.


Actual and Predicted Outcomes
during pretreatment periods in California
cigsale
year
Actual Outcome
Predicted Outcome
Actual and Predicted Outcomes
during posttreatment periods in California
cigsale
year
Actual Outcome
Predicted Outcome
99% Confidence Interval
95% Confidence Interval
90% Confidence Interval
Gaps between Acutal and Predicted Outcomes
during pretreatment periods in California
gaps on cigsale
year
Treatment Effects
during posttreatment periods in California
treatment effects on cigsale
year
Treatment Effect
99% Confidence Interval
95% Confidence Interval
90% Confidence Interval

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Thanks!