# MATLAB Codes and Data for "Half-Panel Jackknife Fixed Effects Estimation of Panels with Weakly Exogenous Regressors"*

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## 1 Overview

This folder contains MATLAB codes and data sets for the Monte Carlo experiments and empirical applications by Chudik, Pesaran and Yang (2016) "Half-Panel Jackknife Fixed Effects Estimation of Panels with Weakly Exogenous Regressors". There are two folders under this one. The folder "Monte Carlo Experiments" contains the MATLAB codes for the Monte Carlo simulations, and the folder "Empirical Applications" containes the MATLAB codes and data sets for the empirical illustrations.

## 2 Monte Carlo Experiments

The folder "Monte Carlo Experiments" contains the MATLAB codes for the Monte Carlo simulations.

### 2.1 Data generating process

Observations on $y_{it}$ and $x_{it}$ are generated *jointly* by

$$y_{it} = \mu_i + \delta_t + \lambda_y y_{i,t-1} + (1-\lambda_y)\beta x_{it} + u_{it}, \tag{1}$$

and

$$x_{it} = (1-\lambda_x)\mu_{ix} + (1-\lambda_x)\kappa_x y_{i,t-1} + \lambda_x x_{i,t-1} + v_{it}, \tag{2}$$

for $i = 1, 2, \ldots, N$ and $t = -99, -98, \ldots, 0, 1, 2, \ldots, T$, using $y_{i,-100} = x_{i,-100} = 0$ as the starting values. The first 100 time observations ($t = -99, -98, \ldots, 0$) are discarded. The fixed effects and the idiosyncratic errors are generated as:

$$\begin{aligned}
\mu_{ix} &\sim IID\mathcal{N}(1,1), \quad \mu_i = \mu_{ix} + \eta_{yi}, \quad \eta_{yi} \sim IID\mathcal{N}(1,1), && (3)\\
v_{it} &\sim IID\mathcal{N}\left(0,\sigma_{vi}^2\right), \quad \sigma_{vi}^2 = 0.5 + 0.25\eta_{vi}^2, \quad \eta_{vi}^2 \sim IID\chi^2(2), && (4)\\
u_{it} &\sim IID\mathcal{N}\left(0,\sigma_{ui}^2\right), \quad \sigma_{ui}^2 = 0.5 + 0.25\eta_{ui}^2, \quad \eta_{ui}^2 \sim IID\chi^2(2). && (5)
\end{aligned}$$

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This set up allows the fixed effects in the $y_{it}$ and $x_{it}$ equations to be correlated, which in turn induces correlation between $\mu_i$ and $x_{it}$. For the time effects, $\delta_t$, we consider three possibilities: no time effects, linear time effects, and quadratic time effects, namely

$$\delta_t = 0,\ 0.025t, \text{ or } 0.025t - 0.001t^2. \tag{6}$$

We consider three values for $\lambda_y$, representing a "static" panel regression with $\lambda_y = 0$, and two dynamic panel regressions with a moderate and high values for $\lambda_y \neq 0$:

$$\lambda_y = 0,\ 0.4, \quad \text{or} \quad 0.8. \tag{7}$$

We also consider three values for the feedback coefficient, $\kappa_x$ (no feedbacks, a low degree of feedbacks, and a medium degree of feedbacks):

$$\kappa_x = 0,\ 0.2, \quad \text{or} \quad 0.4. \tag{8}$$

Throughout we set $\beta = 0.5$ and $\lambda_x = 0.25$.

### 2.2 Experiments without lags of the dependent variable

In the case where $\lambda_y = 0$, *i.e.*, experiments 1 – 9, the parameter of interest, $\beta$ ($= 0.5$), is estimated using the following four estimators:

1. **FE estimator** $\hat{\beta}_{FE}$. In experiments without time effects ($\delta_t = 0$), the FE estimator is based on the panel regression

$$y_{it} = \mu_i + \beta x_{it} + e_{it}. \tag{9}$$

   When $\delta_t = 0.025t$ or $0.025t - 0.001t^2$, the FE estimator is based on

$$y_{it} = \mu_i + gt + \beta x_{it} + e_{it}. \tag{10}$$

   Note that when $\delta_t = 0.025t - 0.001t^2$, the panel regression model (10) is mis-specified.

2. **Half-panel jackknife FE estimator** $\tilde{\beta}_{FE}$.

3. **FE-TE estimator** $\hat{\beta}_{FE-TE}$ is based on

$$y_{it} = \mu_i + \delta_t + \beta x_{it} + e_{it}. \tag{11}$$

4. **Half-panel jackknife FE-TE estimator** $\tilde{\beta}_{FE-TE}$.

### 2.3 Experiments with lagged dependent variables

In these experiments $\lambda_y = 0.4$ or $0.8$, *i.e.*, experiments 10 – 27, the parameter of interest is given by the long-run coefficient, $\beta = -b/\phi$, where $b$ and $\phi$ are estimated using the following dynamic panel regressions:

1. **FE estimator** $\hat{\beta}_{FE}$. When $\delta_t = 0$, $\hat{\beta}_{FE}$ is based on

$$\Delta y_{it} = \mu_i + \phi y_{i,t-1} + b x_{it} + e_{it}, \tag{12}$$

   and when $\delta_t = 0.025t$ or $0.025t - 0.001t^2$, $\hat{\beta}_{FE}$ is based on:

$$\Delta y_{it} = \mu_i + gt + \phi y_{i,t-1} + b x_{it} + e_{it}. \tag{13}$$

   As before, we note that when $\delta_t = 0.025t - 0.001t^2$, the model (13) is mis-specified. $\beta$ is estimated by

$$\hat{\beta}_{FE} = -\frac{\widehat{b}_{FE}}{\widehat{\phi}_{FE}}. \tag{14}$$

   The estimator for the asymptotic variance of $\hat{\beta}_{FE}$ is obtained by the delta method:

$$\widehat{AsyVar}\left(\hat{\beta}_{FE}\right) = \left(\frac{\widehat{b}_{FE}}{\widehat{\phi}^2_{FE}}, -\frac{1}{\widehat{\phi}_{FE}}\right) \widehat{AsyVar}\begin{pmatrix} \widehat{\phi}_{FE} \\ \widehat{b}_{FE} \end{pmatrix} \left(\frac{\widehat{b}_{FE}}{\widehat{\phi}^2_{FE}}, -\frac{1}{\widehat{\phi}_{FE}}\right)'. \tag{15}$$

2. **Half-panel jackknife FE estimator** $\tilde{\beta}_{FE}$. We first compute the half-panel bias-corrected FE estimators $\tilde{\phi}_{FE}$ and $\tilde{b}_{FE}$ based on $\widehat{\phi}_{FE}$ and $\widehat{b}_{FE}$. $\tilde{\beta}_{FE}$ is obtained as

$$\tilde{\beta}_{FE} = -\frac{\tilde{b}_{FE}}{\tilde{\phi}_{FE}},$$

and the estimator for the asymptotic variance of $\tilde{\beta}_{FE}$ is obtained by the delta method similar to (15).

3. **FE-TE estimator** $\hat{\beta}_{FE-TE}$ is based on

$$\Delta y_{it} = \mu_i + \delta_t + \phi y_{i,t-1} + bx_{it} + e_{it}. \tag{16}$$

As in the case of $\hat{\beta}_{FE}$, $\hat{\beta}_{FE-TE} = -\widehat{b}_{FE-TE}/\widehat{\phi}_{FE-TE}$ and its asymptotic variance is obtained by the delta method, as in (15).

4. **Half-panel jackknife FE-TE estimator** $\tilde{\beta}_{FE-TE}$ is computed in the same way as $\tilde{\beta}_{FE}$, but FE-TE estimators are used instead of the FE estimators.

### 2.4 Experiments with unbalanced panels

We also consider unbalanced panels by dropping $[T/5]$ observations from the beginning and from the end of the sample period for units $i = 1, 2, ..., [N/4]$, and $[T/3]$ observations from the beginning and from the end of the sample periods for units $i = [N/4] + 1, [N/4] + 2, ..., [N/2]$, where $[a]$ denotes the integer part of $a$.

### 2.5 Lists of Files

Two folders "Balanced Panels" and "Unbalanced Panels" contain MATLAB files which are used in the Monte Carlo experiments for the cases of balanced samples and unbalanced samples, respectively. In the folder "Balanced Panels" there are 27 files for 27 experiments. For example, the file named

"CPY_Jackknife_MC_Ex01_nolag_not_kappa0.m"

is for the experiment 1. In the folder "Unbalanced Panels" there are 54 files for 27 experiments. For each experiment there are two files for the FE and FETE estimations. For example, the file named

"CPY_Jackknife_MC_Ex01_nolag_not_kappa0_ub_FE.m"

is for the FE estimation for experiment 1, and the file named

"CPY_Jackknife_MC_Ex01_nolag_not_kappa0_ub_FETE.m"

is for the FETE estimation for experiment 1. The full lists of files are summarized in Tables R1 and R2.

## 3 Empirical Applications

The folder "Empirical Applications" contains the MATLAB codes and data sets for the empirical applications. Under this one there are two folders, "Commercial Imperialism" and "Abortion and Crime".

**Table R1: List of Experiments and Files: Balanced Panels**

| Exp. | DGP parameters $\delta_t$ | $\kappa_x$ | $\lambda_y$ | Names of Files: Balanced Panels |
|---|---|---|---|---|
| | Experiments without lagged dependent variable | | | |
| 1 | 0 | 0 | 0 | CPY_Jackknife_MC_Ex01_nolag_not_kappa0.m |
| 2 | 0 | 0.2 | 0 | CPY_Jackknife_MC_Ex02_nolag_not_kappa2.m |
| 3 | 0 | 0.4 | 0 | CPY_Jackknife_MC_Ex03_nolag_not_kappa4.m |
| 4 | $0.025t$ | 0 | 0 | CPY_Jackknife_MC_Ex04_nolag_lineart_kappa0.m |
| 5 | $0.025t$ | 0.2 | 0 | CPY_Jackknife_MC_Ex05_nolag_lineart_kappa2.m |
| 6 | $0.025t$ | 0.4 | 0 | CPY_Jackknife_MC_Ex06_nolag_lineart_kappa4.m |
| 7 | $0.025t - 0.001t^2$ | 0 | 0 | CPY_Jackknife_MC_Ex07_nolag_nonlineart_kappa0.m |
| 8 | $0.025t - 0.001t^2$ | 0.2 | 0 | CPY_Jackknife_MC_Ex08_nolag_nonlineart_kappa2.m |
| 9 | $0.025t - 0.001t^2$ | 0.4 | 0 | CPY_Jackknife_MC_Ex09_nolag_nonlineart_kappa4.m |
| | Experiments with lagged dependent variable | | | |
| 10 | 0 | 0 | 0.4 | CPY_Jackknife_MC_Ex10_1lag_not_lambda4_kappa0.m |
| 11 | 0 | 0.2 | 0.4 | CPY_Jackknife_MC_Ex11_1lag_not_lambda4_kappa2.m |
| 12 | 0 | 0.4 | 0.4 | CPY_Jackknife_MC_Ex12_1lag_not_lambda4_kappa4.m |
| 13 | $0.025t$ | 0 | 0.4 | CPY_Jackknife_MC_Ex13_1lag_lineart_lambda4_kappa0.m |
| 14 | $0.025t$ | 0.2 | 0.4 | CPY_Jackknife_MC_Ex14_1lag_lineart_lambda4_kappa2.m |
| 15 | $0.025t$ | 0.4 | 0.4 | CPY_Jackknife_MC_Ex15_1lag_lineart_lambda4_kappa4.m |
| 16 | $0.025t - 0.001t^2$ | 0 | 0.4 | CPY_Jackknife_MC_Ex16_1lag_nonlineart_lambda4_kappa0.m |
| 17 | $0.025t - 0.001t^2$ | 0.2 | 0.4 | CPY_Jackknife_MC_Ex17_1lag_nonlineart_lambda4_kappa2.m |
| 18 | $0.025t - 0.001t^2$ | 0.4 | 0.4 | CPY_Jackknife_MC_Ex18_1lag_nonlineart_lambda4_kappa4.m |
| 19 | 0 | 0 | 0.8 | CPY_Jackknife_MC_Ex19_1lag_not_lambda8_kappa0.m |
| 20 | 0 | 0.2 | 0.8 | CPY_Jackknife_MC_Ex20_1lag_not_lambda8_kappa2.m |
| 21 | 0 | 0.4 | 0.8 | CPY_Jackknife_MC_Ex21_1lag_not_lambda8_kappa4.m |
| 22 | $0.025t$ | 0 | 0.8 | CPY_Jackknife_MC_Ex22_1lag_lineart_lambda8_kappa0.m |
| 23 | $0.025t$ | 0.2 | 0.8 | CPY_Jackknife_MC_Ex23_1lag_lineart_lambda8_kappa2.m |
| 24 | $0.025t$ | 0.4 | 0.8 | CPY_Jackknife_MC_Ex24_1lag_lineart_lambda8_kappa4.m |
| 25 | $0.025t - 0.001t^2$ | 0 | 0.8 | CPY_Jackknife_MC_Ex25_1lag_nonlineart_lambda8_kappa0.m |
| 26 | $0.025t - 0.001t^2$ | 0.2 | 0.8 | CPY_Jackknife_MC_Ex26_1lag_nonlineart_lambda8_kappa2.m |
| 27 | $0.025t - 0.001t^2$ | 0.4 | 0.8 | CPY_Jackknife_MC_Ex27_1lag_nonlineart_lambda8_kappa4.m |

## 3.1 Commercial Imperialism

Based on Berger, Easterly, Nunn and Satyanath (2013, *American Economic Review*) "Commercial imperialism? political influence and trade during the cold war", we estimate the effect of the US political influence on the bilateral trades of US and foreign countries during the Cold War. The estimating equation is equation (101) of the paper:

$$\ln \frac{m_{it}^{US}}{Y_{it}} = \mu_i + \delta_t + \beta USinfluence_{it} + \phi \ln \tau_{it}^{US} - \phi \left(\ln P_t^{US} + \ln P_t^i\right) + \mathbf{X}_{it}\mathbf{\Gamma} + u_{it}, \tag{17}$$

where the dependent variable, $\ln\left(m_{it}^{US}/Y_{it}\right)$, is the natural log of imports into country $i$ in year $t$ from the US normalized by country $i$'s total GDP. $USinfluence_{it}$ is an indicator variable that equals one, in country $i$ in year $t$, if the CIA (Central Intelligence Agency) either successfully installed a foreign leader or provided covert support for the regime once in power. $\ln \tau_{it}^{US}$ and $\ln P_t^{US} + \ln P_t^i$ respectively denote the trade costs and the multilateral resistance terms, which are given by the distance between US and country $i$, and four indicator variables for US and country $i$ sharing a common language (English), sharing a border, both being GATT (General Agreement on Tariffs and Trade) participants, and belonging to a regional trade agreement. $\mathbf{X}_{it}$ is a vector of control variables including the per capita income of country $i$, an indicator variable for Soviet interventions (constructed in the same manner as CIA interventions), an indicator variable for the change in leadership, a measure of the tenure of the current leader, and an indicator variable for democracy. As Berger *et al.* (2013), we also estimated the effects of CIA interventions on log normalized imports from

## Table R2: List of Experiments and Files: Balanced Panels

| | DGP parameters | | | Names of Files | |
|---|---|---|---|---|---|
| | | | | Balanced Panels | |
| Exp. | $\delta_t$ | $\kappa_x$ | $\lambda_y$ | FE | FETE |
| | Experiments without lagged dependent variable | | | | |
| 1 | 0 | 0 | 0 | CPY_Jackknife_MC_Ex01_nolag_not_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex01_nolag_not_kappa0_ub_FETE.m |
| 2 | 0 | 0.2 | 0 | CPY_Jackknife_MC_Ex02_nolag_not_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex02_nolag_not_kappa2_ub_FETE.m |
| 3 | 0 | 0.4 | 0 | CPY_Jackknife_MC_Ex03_nolag_not_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex03_nolag_not_kappa4_ub_FETE.m |
| 4 | $0.025t$ | 0 | 0 | CPY_Jackknife_MC_Ex04_nolag_lineart_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex04_nolag_lineart_kappa0_ub_FETE.m |
| 5 | $0.025t$ | 0.2 | 0 | CPY_Jackknife_MC_Ex05_nolag_lineart_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex05_nolag_lineart_kappa2_ub_FETE.m |
| 6 | $0.025t$ | 0.4 | 0 | CPY_Jackknife_MC_Ex06_nolag_lineart_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex06_nolag_lineart_kappa4_ub_FETE.m |
| 7 | $0.025t - 0.001t^2$ | 0 | 0 | CPY_Jackknife_MC_Ex07_nolag_nonlineart_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex07_nolag_nonlineart_kappa0_ub_FETE.m |
| 8 | $0.025t - 0.001t^2$ | 0.2 | 0 | CPY_Jackknife_MC_Ex08_nolag_nonlineart_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex08_nolag_nonlineart_kappa2_ub_FETE.m |
| 9 | $0.025t - 0.001t^2$ | 0.4 | 0 | CPY_Jackknife_MC_Ex09_nolag_nonlineart_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex09_nolag_nonlineart_kappa4_ub_FETE.m |
| | Experiments with lagged dependent variable | | | | |
| 10 | 0 | 0 | 0.4 | CPY_Jackknife_MC_Ex10_1lag_not_lambda4_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex10_1lag_not_lambda4_kappa0_ub_FETE.m |
| 11 | 0 | 0.2 | 0.4 | CPY_Jackknife_MC_Ex11_1lag_not_lambda4_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex11_1lag_not_lambda4_kappa2_ub_FETE.m |
| 12 | 0 | 0.4 | 0.4 | CPY_Jackknife_MC_Ex12_1lag_not_lambda4_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex12_1lag_not_lambda4_kappa4_ub_FETE.m |
| 13 | $0.025t$ | 0 | 0.4 | CPY_Jackknife_MC_Ex13_1lag_lineart_lambda4_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex13_1lag_lineart_lambda4_kappa0_ub_FETE.m |
| 14 | $0.025t$ | 0.2 | 0.4 | CPY_Jackknife_MC_Ex14_1lag_lineart_lambda4_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex14_1lag_lineart_lambda4_kappa2_ub_FETE.m |
| 15 | $0.025t$ | 0.4 | 0.4 | CPY_Jackknife_MC_Ex15_1lag_lineart_lambda4_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex15_1lag_lineart_lambda4_kappa4_ub_FETE.m |
| 16 | $0.025t - 0.001t^2$ | 0 | 0.4 | CPY_Jackknife_MC_Ex16_1lag_nonlineart_lambda4_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex16_1lag_nonlineart_lambda4_kappa0_ub_FETE.m |
| 17 | $0.025t - 0.001t^2$ | 0.2 | 0.4 | CPY_Jackknife_MC_Ex17_1lag_nonlineart_lambda4_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex17_1lag_nonlineart_lambda4_kappa2_ub_FETE.m |
| 18 | $0.025t - 0.001t^2$ | 0.4 | 0.4 | CPY_Jackknife_MC_Ex18_1lag_nonlineart_lambda4_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex18_1lag_nonlineart_lambda4_kappa4_ub_FETE.m |
| 19 | 0 | 0 | 0.8 | CPY_Jackknife_MC_Ex19_1lag_not_lambda8_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex19_1lag_not_lambda8_kappa0_ub_FETE.m |
| 20 | 0 | 0.2 | 0.8 | CPY_Jackknife_MC_Ex20_1lag_not_lambda8_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex20_1lag_not_lambda8_kappa2_ub_FETE.m |
| 21 | 0 | 0.4 | 0.8 | CPY_Jackknife_MC_Ex21_1lag_not_lambda8_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex21_1lag_not_lambda8_kappa4_ub_FETE.m |
| 22 | $0.025t$ | 0 | 0.8 | CPY_Jackknife_MC_Ex22_1lag_lineart_lambda8_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex22_1lag_lineart_lambda8_kappa0_ub_FETE.m |
| 23 | $0.025t$ | 0.2 | 0.8 | CPY_Jackknife_MC_Ex23_1lag_lineart_lambda8_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex23_1lag_lineart_lambda8_kappa2_ub_FETE.m |
| 24 | $0.025t$ | 0.4 | 0.8 | CPY_Jackknife_MC_Ex24_1lag_lineart_lambda8_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex24_1lag_lineart_lambda8_kappa4_ub_FETE.m |
| 25 | $0.025t - 0.001t^2$ | 0 | 0.8 | CPY_Jackknife_MC_Ex25_1lag_nonlineart_lambda8_kappa0_ub_FE.m | CPY_Jackknife_MC_Ex25_1lag_nonlineart_lambda8_kappa0_ub_FETE.m |
| 26 | $0.025t - 0.001t^2$ | 0.2 | 0.8 | CPY_Jackknife_MC_Ex26_1lag_nonlineart_lambda8_kappa2_ub_FE.m | CPY_Jackknife_MC_Ex26_1lag_nonlineart_lambda8_kappa2_ub_FETE.m |
| 27 | $0.025t - 0.001t^2$ | 0.4 | 0.8 | CPY_Jackknife_MC_Ex27_1lag_nonlineart_lambda8_kappa4_ub_FE.m | CPY_Jackknife_MC_Ex27_1lag_nonlineart_lambda8_kappa4_ub_FETE.m |

the rest of the world, log normalized exports to the US, and log normalized exports to the rest of the world, with estimating equations derived in an analogous manner as equation (17).

There are eight files in the folder "Commercial Imperialism" .

| | |
|---|---|
| CPY_jackknife_Table9_1b.m | The codes estimating the effect on imports from the US. The results are reported in Table 9, column 1.b. |
| CPY_jackknife_Table9_1b_data.mat | The data set used in CPY_jackknife_Table9_1b.m. |
| CPY_jackknife_Table9_2b.m | The codes estimating the effect on imports from the rest of the world. The results are reported in Table 9, column 2.b. |
| CPY_jackknife_Table9_2b_data.mat | The data set used in CPY_jackknife_Table9_2b.m. |
| CPY_jackknife_Table9_3b.m | The codes estimating the effect on exports to the US. The results are reported in Table 9, column 3.b. |
| CPY_jackknife_Table9_3b_data.mat | The data set used in CPY_jackknife_Table9_3b.m. |
| CPY_jackknife_Table9_4b.m | The codes estimating the effect on exports to the rest of the world. The results are reported in Table 9, column 4.b. |
| CPY_jackknife_Table9_4b_data.mat | The data set used in CPY_jackknife_Table9_4b.m. |

## 3.2 Abortion and Crime

Based on Donohue and Levitt (2001, *Quarterly Journal of Economics*) "The impact of legalized abortion on crime", we estimate the effect of legalized abortion on crimes in the US. There are two estimating equations. The first estimating equation is equation (102) of the paper:

$$y_{it} = \ln(crime_{it}) = \mu_i + \delta_t + \beta_1 ABORT_{it} + \boldsymbol{\psi}'\mathbf{x}_{it} + u_{it}, \tag{18}$$

where $\ln(crime_{it})$ is the logarithm of the crime rate per capita in state $i$ and year $t$. Donohue and Levitt (2001) considered three types of crimes: violent crime, property crime and murders. $ABORT_{it}$, the "effective" legalized abortion rate, and is computed as a weighted average of the abortion rates in which the weights are determined by the fraction of arrests from different age groups. $\mathbf{x}_{it}$ is a vector of control variables, including lagged prisoners and police per capita, a number of variables for state economic conditions, the lagged state welfare generosity, the concealed handgun laws, and per capita beer consumption.

The second estimating equation is equation (103) of the paper:

$$\ln(crime_{it}) = \mu_i + \delta_t + \lambda \ln(crime_{i,t-1}) + \beta_1(1-\lambda)ABORT_{it} + (1-\lambda)\boldsymbol{\psi}'\mathbf{x}_{it} + u_{it}, \tag{19}$$

where $\ln(crime_{i,t-1})$ is the lagged logarithm of crime rate per capita.

The data set is from Belloni, Chernozhukov and Hansen (2014, *Review of Economic Studies*) "Inference on treatment effects after selection among high-dimensional controls". There are five files in the folder "Abortion and Crime" .

| | |
|---|---|
| CPY_jackknife_Table10.m | The codes estimating equation (102) of the paper<br>The results are reported in Table 10. |
| CPY_jackknife_Tables_11_12.m | The codes estimating equation (103) of the paper<br>The results are reported in Tables 11 and 12. |
| CPY_jackknife_Tables_10_11_12_data.dat | The data set used in CPY_jackknife_Table10.m and<br>CPY_jackknife_Tables_11_12.m.<br>The data set is from Belloni *et al.* (2014). |
| dummy.m | The codes written by Belloni *et al.* (2014) to create dummies. |
| recode.m | The codes written by Belloni *et al.* (2014) to recode the data. |