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Fixed-effect panel threshold model using Stata

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Abstract. Threshold models are widely used in macroeconomics and financial analysis for their simple and obvious economic implications. With these models, however, estimation and inference is complicated by the existence of nuisance parameters. To combat this issue, Hansen (1999, *Journal of Econometrics* 93: 345–368) proposed the fixed-effect panel threshold model. In this article, I introduce a new command (`xthreg`) for implementing this model. I also use Monte Carlo simulations to show that, although the size distortion of the threshold-effect test is small, the coverage rate of the confidence interval estimator is unsatisfactory. I include an example on financial constraints (originally from Hansen [1999, *Journal of Econometrics* 93: 345–368]) to further demonstrate the use of `xthreg`.

Keywords: st0373, xthreg, panel threshold, fixed effect

1 Introduction

Heterogeneity is a common problem of panel data. That is to say, each individual in a study is different, and structural relationships may vary across individuals. The classical fixed effect or random effect reflects only the heterogeneity in intercepts. Hsiao (2003) considers many varying slope models for this problem. Among these models, Hansen's (1999) panel threshold model has a simple specification but obvious implications for economic policy. Though threshold models are familiar in time-series analysis, their use with panel data has been limited.

The threshold model describes the jumping character or structural break in the relationship between variables. This model type is popular in nonlinear time series, one example being the threshold autoregressive (TAR) model (Tong 1983). This model can capture many economic phenomena. For example, using five-year interval averages of standard measures of financial development, inflation, and growth for 84 countries from 1960 to 1995, Rousseau and Wachtel (2009) showed that there is an inflation threshold for the finance and growth relationship that lies between 13–25%. When inflation exceeds the threshold, finance ceases to increase economic growth. Inflation's effect on economic growth depends on the inflation level. High levels of inflation are harmful to economic growth, while low levels of inflation are beneficial to economic growth. As another example, the technical spillover of foreign direct investment (FDI) has been widely studied. Girma (2005) found that the productivity benefit from FDI increases with absorptive capacity until some threshold level, at which point it becomes less pronounced. There is also a minimum absorptive capacity threshold level below which productivity spillovers from FDI are negligible or even negative.

This article is arranged as follows. In section 2, I review some basic theories about fixed-effect panel threshold models. I then describe the new `xthreg` command in section 3. In section 4, I perform Monte Carlo simulations to study test-power distortion and the coverage rate of confidence interval estimators in finite samples. I illustrate use of the command with an example from Hansen (1999) in section 5. In section 6, I conclude the article.

2 Fixed-effect panel threshold models

2.1 Single-threshold model

Consider the following single-threshold model:

$$y_{it} = \mu + \mathbf{X}_{it}(q_{it} < \gamma)\boldsymbol{\beta}_1 + \mathbf{X}_{it}(q_{it} \geq \gamma)\boldsymbol{\beta}_2 + u_i + e_{it} \tag{1}$$

The variable q_{it} is the threshold variable, and γ is the threshold parameter that divides the equation into two regimes with coefficients $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$. The parameter u_i is the individual effect, while e_{it} is the disturbance. We can also write (1) as

$$y_{it} = \mu + \mathbf{X}_{it}(q_{it}, \gamma)\boldsymbol{\beta} + u_i + e_{it}$$

where

$$\mathbf{X}_{it}(q_{it}, \gamma) = \begin{cases} \mathbf{X}_{it} I(q_{it} < \gamma) \\ \mathbf{X}_{it} I(q_{it} \geq \gamma) \end{cases}$$

Given γ, the ordinary least-squares estimator of $\boldsymbol{\beta}$ is

$$\widehat{\boldsymbol{\beta}} = \{\boldsymbol{X}^*(\gamma)'\boldsymbol{X}^*(\gamma)\}^{-1}\{\boldsymbol{X}^*(\gamma)'\boldsymbol{y}^*\}$$

where $\boldsymbol{y}^*$ and $\boldsymbol{X}^*$ are within-group deviations. The residual sum of squares (RSS) is equal to $\widehat{e}^{*\prime}\widehat{e}^*$. To estimate γ, one can search over a subset of the threshold variable q_{it}. Instead of searching over the whole sample, we restrict the range within the interval $(\underline{\gamma}, \overline{\gamma})$, which are quantiles of q_{it}. γ's estimator is the value that minimizes the RSS, that is,

$$\widehat{\gamma} = \arg\min_{\gamma} S_1(\gamma)$$

If γ is known, the model is no different from the ordinary linear model. But if γ is unknown, there is a nuisance parameter problem, which makes the γ estimator's distribution nonstandard. Hansen (1999) proved that $\widehat{\gamma}$ is a consistent estimator for γ, and he argued that the best way to test $\gamma = \gamma_0$ is to form the confidence interval using the "no-rejection region" method with a likelihood-ratio (LR) statistic, as follows:

$$\begin{aligned} \mathrm{LR}_1(\gamma) &= \frac{\{\mathrm{LR}_1(\gamma) - \mathrm{LR}_1(\widehat{\gamma})\}}{\widehat{\sigma}^2} \xrightarrow{\Pr} \xi \\ \Pr(x < \xi) &= (1 - e^{\frac{-x}{2}})^2 \end{aligned} \tag{2}$$

Given significance level α, the lower limit corresponds to the maximum value in the LR series, which is less than the α quantile, and the upper limit corresponds to the minimum value in the LR series, which is less than the α quantile. The α quantile can be computed from the following inverse function of (2):

$$c(\alpha) = -2 \log \left(1 - \sqrt{1-\alpha}\right)$$

For example, for $\alpha = 0.1$, 0.05, and 0.01, the quantiles are 6.53, 7.35, and 10.59, respectively. If $\mathrm{LR}_1(\gamma_0)$ exceeds $c(\alpha)$, then we reject H_0.

Testing for a threshold effect is the same as testing for whether the coefficients are the same in each regime. The null hypothesis and the alternative hypothesis (the linear versus the single-threshold model) are

$$H_0 : \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 \quad H_a : \boldsymbol{\beta}_1 \neq \boldsymbol{\beta}_2$$

The F statistic is constructed as

$$F_1 = \frac{(S_0 - S_1)}{\widehat{\sigma}^2} \tag{3}$$

Under H_0, the threshold γ is not identified, and F_1 has nonstandard asymptotic distribution. We use bootstrap on the critical values of the F statistic to test the significance of the threshold effect. S_0 is the RSS of the linear model. Hansen (1996) suggested the following bootstrap design:

Step 1: Fit the model under H_a and obtain the residual $\widehat{e}^*_{it}$.

Step 2: Make a cluster resampling $\widehat{e}^*_{it}$ with replacement, and obtain the new residual v^*_{it}.

Step 3: Generate a new series under the H_a data-generating process (DGP), $y^*_{it} = \mathbf{X}^*_{it}\boldsymbol{\beta} + v^*_{it}$, where $\boldsymbol{\beta}$ can take arbitrary values.

Step 4: Fit the model under H_0 and H_a, and compute the F statistic using (3).

Step 5: Repeat steps 1–4 B times, and the probability of F is $\Pr = I(F > F_1)$, namely, the proportion of $F > F_1$ in bootstrap number B.

2.2 Multiple-thresholds model

If there are multiple thresholds (that is, multiple regimes), we fit the model sequentially. We use a double-threshold model as an example.

$$y_{it} = \mu + \mathbf{X}_{it}(q_{it} < \gamma_1)\boldsymbol{\beta}_1 + \mathbf{X}_{it}(\gamma_1 \leq q_{it} < \gamma_2)\boldsymbol{\beta}_2 + \mathbf{X}_{it}(q_{it} \geq \gamma_2)\boldsymbol{\beta}_3 + u_i + e_{it}$$

Here, γ_1 and γ_2 are the thresholds that divide the equation into three regimes with coefficients $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, and $\boldsymbol{\beta}_3$. We need to compute this $(N \times T)^2$ times using the grid search method, which is infeasible in practice. According to Bai (1997) and Bai and Perron (1998), the sequential estimator is consistent, so we estimate the thresholds as follows:

Step 1: Fit the single-threshold model to obtain the threshold estimator γ_1 and the RSS $S_1(\widehat{\gamma}_1)$.

Step 2: Given $\widehat{\gamma}_1$, the second threshold and its confidence interval are

$$
\begin{aligned}
\widehat{\gamma}_2^r =& \arg\min_{\gamma_2} \{S_2^r(\gamma_2)\} \\
S_2^r =& S\{\min(\widehat{\gamma}_1, \gamma_2)\max(\widehat{\gamma}_1, \gamma_2)\} \\
\mathrm{LR}_2^r(\gamma_2) =& \frac{\{S_2^r(\gamma_2) - S_2^r(\widehat{\gamma}_2^r)\}}{\widehat{\sigma}_{22}^2}
\end{aligned}
$$

Step 3: $\widehat{\gamma}_2^r$ is efficient but $\widehat{\gamma}_1^r$ is not. We reestimate the first threshold as

$$
\begin{aligned}
\widehat{\gamma}_1^r =& \arg\min_{\gamma_1} \{S_1^r(\gamma_1)\} \\
S_1^r =& S\{\min(\gamma_1, \widehat{\gamma}_2)\max(\gamma_1, \widehat{\gamma}_2)\} \\
\mathrm{LR}_1^r(\gamma_1) =& \frac{\{S_1^r(\gamma_1) - S_1^r(\widehat{\gamma}_1^r)\}}{\widehat{\sigma}_{21}^2}
\end{aligned}
$$

The threshold-effect test is also sequential; that is, if we reject the null hypothesis in a single-threshold model, then we must test the double-threshold model. The null hypothesis is a single-threshold model, and the alternative hypothesis is a double-threshold model. The F statistic is constructed as

$$
F_2 = \frac{\{S_1(\widehat{\gamma}_1) - S_2^r(\widehat{\gamma}_2^r)\}}{\widehat{\sigma}_{22}^2} \tag{4}
$$

The bootstrapping design for this is similar to that in the single-threshold model. In step 3, we generate a new series under the H_0 DGP, $y_{it}^* = \mathbf{X}_{it}^* \boldsymbol{\beta}_S + v_{it}^*$. The estimator $\boldsymbol{\beta}_S$ is the estimator in a single-threshold model, that is, under the H_a DGP. We use the predicted values.

For models with more than two threshold parameters, the process is similar. Chan (1993) and Hansen (1999) show that the dependence of the estimation and inference of $\boldsymbol{\beta}$ on the threshold estimate is not of first-order asymptotic importance, so the inference of $\boldsymbol{\beta}$ can proceed because γ is given.

3 The xthreg command

3.1 Syntax

`xthreg` *depvar* [*indepvars*] [*if*] [*in*], `rx(`*varlist*`)` `qx(`*varname*`)` [`thnum(`#`)` `grid(`#`)` `trim(`*numlist*`)` `bs(`*numlist*`)` `thlevel(`#`)` `gen(`*newvarname*`)` `noreg` `nobslog` `thgiven` *options*]

where *depvar* is the dependent variable and *indepvars* are the regime-independent variables.

3.2 Options

`rx(`*varlist*`)` is the regime-dependent variable. Time-series operators are allowed. `rx()` is required.

`qx(`*varname*`)` is the threshold variable. Time-series operators are allowed. `qx()` is required.

`thnum(`#`)` is the number of thresholds. In the current version (Stata 13), # must be equal to or less than 3. The default is `thnum(1)`.

`grid(`#`)` is the number of grid points. `grid()` is used to avoid consuming too much time when computing large samples. The default is `grid(300)`.

`trim(`*numlist*`)` is the trimming proportion to estimate each threshold. The number of trimming proportions must be equal to the number of thresholds specified in `thnum()`. The default is `trim(0.01)` for all thresholds. For example, to fit a triple-threshold model, you may set `trim(0.01 0.01 0.05)`.

`bs(`*numlist*`)` is the number of bootstrap replications. If `bs()` is not set, `xthreg` does not use bootstrap for the threshold-effect test.

`thlevel(`#`)` specifies the confidence level, as a percentage, for confidence intervals of the threshold. The default is `thlevel(95)`.

`gen(`*newvarname*`)` generates a new categorical variable with 0, 1, 2, ... for each regime. The default is `gen(_cat)`.

`noreg` suppresses the display of the regression result.

`nobslog` suppresses the iteration process of the bootstrap.

`thgiven` fits the model based on previous results.

options are any options available for `xtreg` (see [XT] **xtreg**).

Time-series operators are allowed in *depvar*, *indepvars*, `rx()`, and `qx()`.

3.3 Stored results

`xthreg` uses `xtreg` (see [XT] **xtreg**) to fit the fixed-effect panel threshold model given the threshold estimator. Along with the standard stored results from `xtreg`, `xthreg` also stores the following results in `e()`:

Scalars	
`e(thnum)`	number of thresholds
`e(grid)`	number of grid search points
Macros	
`e(depvar)`	name of dependent variable
`e(ix)`	regime-independent variables
`e(rx)`	regime-dependent variables
`e(qx)`	threshold variable
Matrices	
`e(Thrss)`	threshold estimator and confidence interval
`e(Fstat)`	threshold-effect test result
`e(bs)`	bootstrap number
`e(trim)`	trimming proportion
`e(LR)`	LR statistics for single-threshold model
`e(LR_2_1)`	LR statistics for first threshold in double-threshold model
`e(LR_2_2)`	LR statistics for second threshold in double-threshold model
`e(LR3)`	LR statistics for third threshold in triple-threshold model

The fixed-effect panel threshold model requires balanced panel data, which is checked automatically by `xthreg`. The estimation and test of the threshold effect are computed in Mata.

You can fit the model with more thresholds using the previous result. For example, assume you use `xthreg` to fit a single-threshold model by using `thnum(1)`, but the single threshold is not sufficient to capture the nonlinear effect. To now fit a double-threshold model, you can run the `xthreg` command using `thgiven`. Stata will search the second threshold using the previous result and will not fit the single-threshold model. I illustrate this in the example below.

4 Monte Carlo simulation

`xthreg` implements the method by Hansen (1999), in which the bootstrap method is used to test the null hypothesis of no threshold. Under the null, the distribution is continuous, so the bootstrap method can be applied. However, there is no formal justification for using the bootstrap test with a multiple-threshold model. Moreover, if bootstrap is used to create confidence intervals for the threshold model, then there may be a problem.

Enders, Falk, and Siklos (2007) compared the finite-sample performance of the following three methods in TAR: inverting the LR statistic using the asymptotic critical values, using the bootstrapped distribution of the LR to determine the critical values, and using the bootstrap percentile method. They found that none of the three methods performs satisfactorily for the discontinuous-TAR model. All three methods are too conservative, creating confidence intervals that are too wide. Of the methods, the bootstrapped LR method performs the worst.

However, new bootstrap methods for the TAR model have recently been introduced. Gonzalo and Wolf (2005) proposed to use a subsampling method—like that introduced by Politis, Romano, and Wolf (1999)—to improve the finite-sample performance of the threshold estimator in the self-exciting TAR model. Andrews and Guggenberger (2009) then introduced a hybrid subsampling method and size-corrected methods of constructing tests and confidence intervals that have correct asymptotic size. However, literature concerning the panel threshold model is still very limited, and there is still no theoretical development for overcoming wide confidence intervals. Following Hansen (1999), I invert the LR statistic to construct the confidence interval of the threshold estimator. Hansen (1999) did not perform Monte Carlo simulations to study the coverage rate for this method.

In this section, I perform simulations to study the size of the threshold-effect test and the coverage rate of the threshold estimator. For the real significance level of the threshold-effect test, the DGP for the null hypothesis (without the threshold effect) is simply a linear regression model, that is,

$$y_{it} = 1 + z_{it} + x_{it} + u_i + e_{it}$$

The variables are generated according to $z_{it}, x_{it} \sim \chi^2(1), u_i \sim \chi^2(1) - 1$, and $e_{it} \sim N(0, 1)$, where z is regime independent and x is regime dependent. The alternative hypothesis is that the coefficient of x is regime dependent on some threshold variable q. We set $n = 50$, 100, 200, 500 and $T = 5$, 20, 50. The bootstrap iteration number is set to 300 for this single-threshold model. The iteration number of Monte Carlo simulation is set to 500.

The simulation is time consuming because bootstrap is used to test the threshold effect for each simulation. On a computer with Inter Core i7, 2.22 GHz processor, and 8 GB RAM, the simulation takes about 26 hours. Table 1 lists the result.

The test size distortion is small, even for small n and T. However, there is no convergence of the bias with increasing sample sizes. As Hansen (1997) noted, "the bootstrap procedure attains the first-order asymptotic distribution, so p-values constructed from the bootstrap are asymptotically valid. Because the asymptotic distribution is nonpivotal, bootstrap size will not have an accelerated rate of convergence relative to conventional asymptotic approximations."

Table 1. Simulation result of the size of the threshold-effect test

n	T	1%	5%	10%
50	5	0.010	0.064	0.118
100	5	0.024	0.062	0.114
200	5	0.022	0.058	0.094
500	5	0.008	0.048	0.106
50	20	0.012	0.050	0.108
100	20	0.016	0.046	0.090
200	20	0.008	0.040	0.098
500	20	0.014	0.058	0.122
50	50	0.014	0.058	0.108
100	50	0.012	0.044	0.114
200	50	0.010	0.048	0.102
500	50	0.014	0.056	0.122

The following DGP is used to simulate the coverage rate where $q_{it} \sim \chi^2(1)$:

$$y_{it} = 1 + z_{it} + x_{it}(q_{it} < 1) + 2x_{it}(q_{it} \geq 1) + u_i + e_{it}$$

The iteration number of Monte Carlo simulation is set to 500. The result is given in table 2.

Table 2. Simulation result of the coverage rate

n	T	RMSE	Rate	n	T	RMSE	Rate	n	T	RMSE	Rate
50	5	0.0103	0.460	50	20	0.00040	0.808	50	50	0.00010	0.952
100	5	0.0026	0.636	100	20	0.00005	0.920	100	50	0.00005	0.994
200	5	0.0005	0.768	200	20	0.00003	0.988	200	50	0.00003	1.000
500	5	0.0001	0.948	500	20	0.00001	0.998	500	50	0.00002	1.000

Obviously, the root of the mean squared error decreases with larger n or larger T. Figure 1 is the kernel density plot of the estimators for $n = 50$, 100, 200, 500 and $T = 5$, which demonstrates the consistency of the estimator. Because of the consistency of the threshold estimator, the estimators of the regression coefficient given the threshold are consistent with the ordinary linear fixed-effect model. However, as n or T increases, the confidence interval gets wider and the coverage rate of the threshold estimator gets bigger than the nominal level. This means that the confidence interval gets too wide for large n and T, because the inverse LR method is not a very efficient method for constructing confidence intervals. As previously discussed, this problem is not specific to the panel threshold model; it is common to almost all threshold models. In sum, the inverse LR method does not perform that well for small sample sizes, and more research is needed to improve the coverage rate for the panel threshold model.

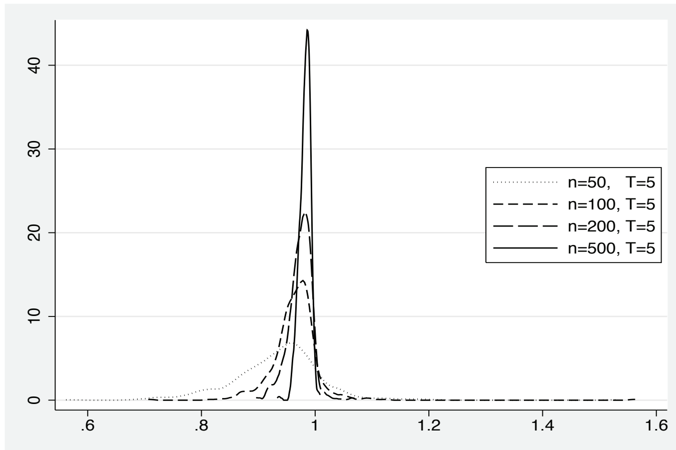

Figure 1. Kernel density of threshold estimator for different samples with real $\gamma = 1$

5 Example

Financing constraints are widely researched. The basic idea is that a firm's cash flow will be positively related to its investment rate only when the firm faces constraints on external financing. If a firm is free to borrow on external financial markets, cash flow will be irrelevant for investment. The dividend-to-income ratio is often used as an indicator; that is, a financially constrained firm will choose to retain earnings rather than pay dividends. Hence, the firms that have low levels of dividend payments are the financially constrained firms.

Hansen (1999) applied the fixed-effect panel threshold model to a 15-year sample of 565 U.S. firms to test whether financial constraints affect investment decisions. Hansen fit the following model:

$$\begin{aligned} I_{it} &= \beta_0 + \beta_1 q_{it-1} + \beta_2 q_{it-1}^2 + \beta_3 q_{it-1}^3 + \beta_4 d_{it-1} + \beta_5 q_{it-1} d_{it-1} + \beta_6 c_{it-1} I(d_{it-1} < \gamma_1) \\ &\quad + \beta_7 c_{it-1} I(\gamma_1 \le d_{it-1} < \gamma_2) + \beta_8 c_{it-1} I(d_{it-1} \ge \gamma_2) + u_i + e_{it} \end{aligned}$$

The variable I_{it} is the investment-to-capital ratio, q_{it} is the ratio of total market value to assets, c_{it} is the ratio of cash flow to assets, and d_{it} is the long-term debt-to-asset ratio.

First, we fit a single-threshold model. The threshold variable `d1` is trimmed off 5% at both sides to be searched for the threshold estimator. We use `grid(400)` to reduce the computation cost. The bootstrap number is set to `bs(300)`.

```
. use hansen1999, clear
(The Value and Performance of U.S. Corporations (B.H.Hall & R.E.Hall, 1993))
. xthreg i q1 q2 q3 d1 qd1, rx(c1) qx(d1) thnum(1) grid(400) trim(0.01) bs(300)
Estimating  the  threshold  parameters:   1st ......  Done
Boostrap for single threshold
.................................................. +   50
.................................................. +  100
.................................................. +  150
.................................................. +  200
.................................................. +  250
.................................................. +  300

Threshold estimator (level = 95):
-----------------------------------------------------
     model |   Threshold         Lower         Upper
-----------+-----------------------------------------
      Th-1 |      0.0154        0.0141        0.0167
-----------------------------------------------------

Threshold effect test (bootstrap = 300):
-------------------------------------------------------------------------------
 Threshold |       RSS        MSE      Fstat    Prob   Crit10    Crit5    Crit1
-----------+-------------------------------------------------------------------
    Single |   17.7818     0.0023      35.20  0.0033  11.9749  14.0259  22.8402
-------------------------------------------------------------------------------

Fixed-effects (within) regression               Number of obs      =      7910
Group variable: id                              Number of groups   =       565

R-sq:  within  = 0.0951                         Obs per group: min =        14
       between = 0.0692                                        avg =      14.0
       overall = 0.0660                                        max =        14

                                                F(7,7338)          =    110.21
corr(u_i, Xb)  = -0.3972                        Prob > F           =    0.0000

------------------------------------------------------------------------------
           i |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q1 |   .0105555   .0008917    11.84   0.000     .0088075    .0123035
          q2 |  -.0202872   .0025602    -7.92   0.000     -.025306   -.0152683
          q3 |   .0010785   .0001952     5.53   0.000     .0006959    .0014612
          d1 |  -.0229482   .0042381    -5.41   0.000     -.031256   -.0146403
         qd1 |   .0007392   .0014278     0.52   0.605    -.0020597    .0035381
             |
   _cat#c.c1 |
           0 |   .0552454   .0053343    10.36   0.000     .0447885    .0657022
           1 |   .0862498   .0052022    16.58   0.000      .076052    .0964476
             |
       _cons |   .0628165   .0016957    37.05   0.000     .0594925    .0661405
-------------+----------------------------------------------------------------
     sigma_u |  .03980548
     sigma_e |  .04922656
         rho |  .39535508   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(564, 7338) =     6.90           Prob > F = 0.0000
```

The output consists of four parts. The first part outputs the estimation and bootstrap results. The second part outputs the threshold estimators and their confidence intervals. `Th-1` denotes the estimator in single-threshold models. In the `threshold estimator` table, `Th-21` and `Th-22` denote the two estimators in a double-threshold model. Sometimes, `Th-21` is the same as `Th-1`. The third part lists the threshold-effect test, including the `RSS`, the mean squared error (`MSE`), the F statistic (`Fstat`), the probability value of the F statistic (`Prob`), and critical values at 10%, 5%, and 1% significance levels (`Crit10`, `Crit5`, and `Crit1`, respectively). The fourth part outputs the fixed-effect regression.

In this example, the single-threshold model's estimator is 0.0154 with 95% confidence interval [0.0141, 0.0167]. The F statistic is highly significant. Therefore, we reject the linear model and fit a double- or triple-threshold model.

Next, we directly fit a triple-threshold model based on the result above. The trimming values are set to be 0.01 and 0.05 for the estimation of the second and third thresholds. Note that the trimming proportion (0.01) for the single-threshold model still needs to be set because `xthreg` searches the second threshold using the trimmed series in the single-threshold model. We set the bootstrap number to 300 for the double- and triple-threshold models; however, we set this to `0` for the single-threshold model because there is no need to use bootstrap for it again (the full option is `bs(0 300 300)`). We suppress the output of bootstrap replications and the fixed-effect regression.

```
. xthreg i q1 q2 q3 d1 qd1, rx(c1) qx(d1) thnum(3) grid(400) trim(0.01 0.01 0.05
> ) bs(0 300 300) thgiven nobslog noreg
Estimating  the  threshold  parameters:   2nd ......  3rd ......  Done
Boostrapping for threshold effect test:   2nd ......  3rd ......  Done
Threshold estimator (level = 95):
```

model	Threshold	Lower	Upper
Th-1	0.0154	0.0141	0.0167
Th-21	0.0154	0.0141	0.0167
Th-22	0.5418	0.5268	0.5473
Th-3	0.4778	0.4755	0.4823

```
Threshold effect test (bootstrap = 0 300 300):
```

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	17.7818	0.0023	35.20	0.0033	11.9749	14.0259	22.8402
Double	17.7258	0.0022	24.97	0.0133	10.8901	12.8409	27.6450
Triple	17.7119	0.0022	6.20	0.5933	16.8006	21.8740	31.6187

Note that `xthreg` gets a similar but not identical F statistic because of the randomness of bootstrap sampling. Of course, this does not affect the conclusion. In the threshold-effect test table, `Single` corresponds to H_0 (linear model) and H_a (single-threshold model), `Double` corresponds to H_0 (single-threshold model) and H_a (double-threshold model), and so forth. Obviously, the double-threshold model is accepted with probability value 0.59.

We can view the threshold confidence interval by plotting the LR statistic.

```
. _matplot e(LR21), columns(1 2) yline(7.35, lpattern(dash))
>         connect(direct) msize(small) mlabp(0) mlabs(zero)
>         ytitle("LR Statistics") xtitle("First Threshold") recast(line) name(L
> R21) nodraw
. _matplot e(LR22), columns(1 2) yline(7.35, lpattern(dash))
>         connect(direct) msize(small) mlabp(0) mlabs(zero)
>         ytitle("LR Statistics") xtitle("Second Threshold") recast(line) name(
> LR22) nodraw
. graph combine LR21 LR22, cols(1)
```

In figure 2, the dashed line denotes the critical value (7.35) at the 95% confidence level.

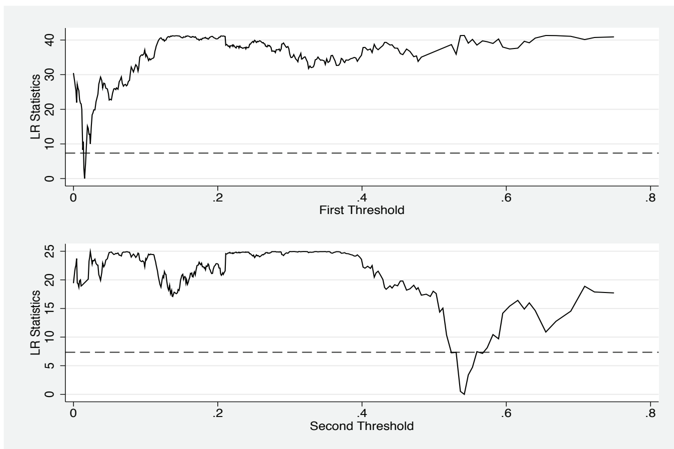

Figure 2. LR statistic of two thresholds

We can also directly fit a triple-threshold model by using the following command:

```
. xthreg i q1 q2 q3 d1 qd1, rx(c1) qx(d1) thnum(3) grid(400)
> trim(0.01 0.01 0.05) bs(300 300 300) nobslog noreg
```

(*output omitted*)

6 Conclusion

The threshold model is a valuable tool for studying many economic phenomena, and the panel threshold model has been widely used in financial and macroeconomic fields. In this article, I introduced the new `xthreg` command, which fits the fixed-effect panel threshold model—a threshold model that could also be a useful tool in financial and economic research. I performed Monte Carlo simulations to exemplify the effectiveness of using the bootstrap method in the threshold model, as originally suggested by Hansen (1999). When using these methods, the significance test level of the threshold effect is very near to the nominal significance test level. I also showed that the threshold estimator is consistent but the confidence interval gets wider and the coverage rate of the threshold estimator gets bigger than the nominal level as n or T increases.

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