Testing and Estimating Structural Breaks in Time Series and Panel Data in Stata

Jan Ditzen
Free University of Bozen-Bolzano
Bozen/Italy
jan.ditzen@unibz.it

Yiannis Karavias
University of Birmingham
Birmingham/UK
i.karavias@bham.ac.uk

Joakim Westerlund
Lund University
Lund/Sweden
joakim.westerlund@nek.lu.se

and
Deakin University
Melbourne/Australia
j.westerlund@deakin.edu.au

Abstract. Identifying structural change is a crucial step in analysis of time series and panel data. The longer the time span, the higher the likelihood that the model parameters have changed as a result of major disruptive events, such as the 2007–2008 financial crisis and the 2020 COVID–19 outbreak. Detecting the existence of breaks, and dating them is therefore necessary not only for estimation purposes but also for understanding drivers of change and their effect on relationships. This article introduces a new community contributed command called \texttt{xtbreak}, which provides researchers with a complete toolbox for analysing multiple structural breaks in time series and panel data. \texttt{xtbreak} can detect the existence of breaks, determine their number and location, and provide break date confidence intervals. The new command is used to explore changes in the relationship between COVID–19 cases and deaths in the US using both country-level time series data and state-level panel data.

Keywords: Structural breaks; Time series data; Panel data; Cross-section dependence; COVID–19; \texttt{xtbreak}.

1 Introduction

In economics and elsewhere linear relationships between dependent and explanatory variables are at the core of interest. To investigate such relationships, observations over time for one or more cross-sectional units such as firms, individuals, or countries are collected and are subsequently used in estimating the coefficients of regression models. A key assumption here is that the coefficients do not change over time. This assumption is unlikely to hold, especially for longer periods of time, because of major disruptive
events, such as financial crises. Parameter instability can have a detrimental impact on estimation and inference, and can lead to costly errors in decision-making. The times in which the parameters change are called “change points” in the statistics literature and “structural breaks” in economics. As both terms are synonymous to each other, in the following we will use the latter term or just “breaks”.

The aim of this paper is to propose a new community contributed Stata package called \texttt{xtbreak}. The package implements the methods developed by Bai and Perron (1998) for the case of pure time series, and Ditzen et al. (2021) in the case of panel data.

\texttt{xtbreak} provides researchers with a complete toolbox for analysing multiple structural breaks in time series and panel data. It can detect and date an unknown number of breaks at unknown break dates. The toolbox is based on asymptotically valid tests for the presence of breaks, a consistent break date estimator, and a break date confidence interval with correct asymptotic coverage. In fact, \texttt{xtbreak} includes no less than three tests: (i) a test of no structural change against the alternative of a specific number of changes, (ii) a test the null hypothesis of no structural change against the alternative of an unknown number of structural changes, and (iii) a test of the null of \( s \) changes against the alternative of \( s + 1 \) changes. The package also includes an algorithm that employs the last test consecutively in order to estimate the true number of breaks. The tested break dates can be unknown or user-defined, as when researchers have additional information and wish to examine whether there was a break in a specific point in time. Once the presence of breaks has been tested and confirmed, \texttt{xtbreak} estimates the locations of the breaks and provides the associated confidence intervals.

A large number of breaks does not translate into heavy computational burden, as \texttt{xtbreak} implements an efficient dynamic programming method described in Bai and Perron (2003), which ensures that there are \( O(T^2) \) computations, even with more than two breaks.

\texttt{xtbreak} can deal with models of “pure” or “partial” structural change. A pure structural change model is one in which the coefficients of all explanatory variables change, while in a partial structural change model only a subset of the coefficients change.

\texttt{xtbreak} is applicable used under very general conditions. In case of panel data, the tools can be used even if the model errors are dependent and heteroskedastic across both time and cross-sectional units. The cross-sectional dependence is assumed to have an “interactive effects”, or “common factor”, structure, which means that the dependence is of the strong form. We also allow the regressors to load on the same set of factors as the errors, which means that they may be endogenous. The allowable dependencies over time are also very general. The only requirement is that they cannot be strong, as in the presence of unit roots.

1. Updates will be continuously provided on our GitHub page: [GitHub](https://github.com).
2. The [Ditzen et al. (2021)](https://www.jstor.org/stable/10.1080/00472494.2021.1943587) study builds on earlier work by [Karavias et al. (2021)](https://www.jstor.org/stable/10.1080/00472494.2021.1943587) in the case of a single break.
The works of Bai and Perron (1998), and Ditzen et al. (2021) draw on the economics literature. However, structural breaks are not confined to economics but happen also in other fields of research, including engineering, epidemiology, climatology, and medicine. xtabreak is therefore widely applicable. To showcase this width, we consider as an example the epidemiological relationship between COVID–19 cases and deaths. Using both aggregate country and disaggregated state level US data, we find evidence of multiple breaks. In particular, we find that an increase in the number of COVID–19 cases lead to more deaths in the beginning of the pandemic than in later waves.

The remainder of the paper is organized as follows: Section 2 presents the model that we will be considering. We focus on the panel case, which in most regards includes the pure time series setup as a special case. Important differences are brought up and discussed. Section 3 presents the hypothesis tests and Section 4 the break estimation procedure. Section 5 presents the xtabreak command. Section 6 contains the empirical analysis of the relationship between COVID–19 cases and deaths. Section 7 concludes the paper. Section 8 includes instructions on installing xtabreak, and Sections 9 and 10 contain acknowledgements and references, respectively.

2 Model discussion

We consider the following model with \( N \) units, \( T \) periods and \( s \) structural breaks:

\[
y_{i,t} = x'_{i,t} \beta + w'_{i,t} \delta_j + e_{i,t}, \tag{1}
\]

where \( t = T_{j-1}, ..., T_j \) and \( j = 1, ..., s + 1 \) with \( T_0 = 0 \) and \( T_{s+1} = T \). Hence, there are \( s \) breaks, or \( s + 1 \) regimes with regime \( j \) covering the observations \( T_{j-1}, ..., T_j \). In order to emphasise the break structure, we can write (1) regime-wise:

\[
y_{i,t} = x'_{i,t} \beta + w'_{i,t} \delta_1 + e_{i,t} \text{ for } t = T_0, ..., T_1,
\]

\[
y_{i,t} = x'_{i,t} \beta + w'_{i,t} \delta_2 + e_{i,t} \text{ for } t = T_1, ..., T_2,
\]

\[
\vdots
\]

\[
y_{i,t} = x'_{i,t} \beta + w'_{i,t} \delta_{s+1} + e_{i,t} \text{ for } t = T_s, ..., T_{s+1}.
\]

For \( N = 1 \), this is a time series model, while for \( N > 1 \), it is a panel data model. The dependent variable \( y_{i,t} \) and the regression error \( e_{i,t} \) are scalars, while \( x_{i,t} \) and \( w_{i,t} \) are \( p \times 1 \) and \( q \times 1 \) vectors, respectively, of regressors. The coefficients of the regressors in \( x_{i,t} \) are unaffected by the breaks, while those of \( w_{i,t} \) are affected by the breaks. It is possible that all independent variables break, in which case \( x'_{i,t} \beta \) is defined to be zero. The break dates are common for all units. This is a very common assumption that is reasonable in settings where the frequency of the data is not high. Let \( T_s = \{T_1, ..., T_s\} \) be a collection of \( s \) break dates such that \( T_j = [\lambda_j T] \), where \( \lambda_0 = 0 < \lambda_1 < ... < \lambda_s < \lambda_{s+1} = 1 \). By specifying the breaks in this way we ensure that they are distinct from one another and that they are bounded away from the beginning and end of the sample. This is important because we need to be able to estimate the model within each regime.
In case the data has a panel structure ($N > 1$), we allow for unobserved heterogeneity in the form of interactive effects:

$$
e_{i,t} = f_t' \gamma_i + \epsilon_{i,t},$$

(2)

where $f_t$ is an $m \times 1$ vector of factors and $\gamma_i$ is a conformable vector of factor loadings. The fact that $f_t$ is common to all cross-sectional units $i$ means that the regression errors can be strongly cross-sectionally correlated. This specification is very general and nests the usual one-way and two-way fixed effects models as special cases. Both $f_t$ and $\epsilon_{i,t}$ may be weakly serially correlated, but they cannot be correlated with each other and $\epsilon_{i,t}$ cannot be cross-sectionally correlated. This ensures that any cross-section dependence in $e_{i,t}$ originates with $f_t$.

Typically there is a lot of cross-sectional co-movement not only in the regression errors but also in the regressors. To account for this, we assume that $x_{i,t}$ and $w_{i,t}$ are generated in the following way:

$$x_{i,t} = \Gamma'_{x,i} f_t + u_{x,i,t},$$

(3)

$$w_{i,t} = \Gamma'_{w,i} f_t + u_{w,i,t},$$

(4)

where $\Gamma_{x,i}$ and $\Gamma_{w,i}$ are $p \times m$ and $q \times m$ matrices, respectively, of factor loadings, while $u_{x,i,t}$ and $u_{w,i,t}$ are $p \times 1$ and $q \times 1$ vectors, respectively, of idiosyncratic errors that are independent of all the other random elements of the model. The model described by (1)–(4) above is the same as the one considered by Ditzen et al. (2021).

The fact that $x_{i,t}$ and $w_{i,t}$ are allowed to load on the same set of factors as $e_{i,t}$ means that they can be endogenous. This type of endogeneity through unobserved heterogeneity is standard in panel data. Here we are considering interactive effects, but the idea is the same in the fixed effects case; the effects sitting in errors might also be in the regressors, which means that they have to be removed prior to estimation. In the fixed effects case, one augments (1) by dummy variables, which is tantamount to transforming the variables into deviations from means. Here a more elaborate augmentation approach is needed, as to be expected since interactive effects are more general than fixed effects. Had the factors been known, which would be the case if i.e. the unobserved heterogeneity is made up of known deterministic terms, we would have estimated

$$y_{i,t} = x_{i,t}' \beta + w_{i,t}' \delta_j + f_t' \gamma_i + \epsilon_{i,t}$$

(5)

by ordinary least squares (OLS). This is possible because with $f_t$ as a regressor the regression error is no longer given by $e_{i,t}$ but by $\epsilon_{i,t}$, which is independent of the regressors. If, on the other hand, $f_t$ is not known, then we need a good proxy to use in

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3. We use the term “unobserved heterogeneity”, although $f_t$ might be known. Later on we elaborate on this.
4. The factor-in-regressors condition rules out lags of the dependent variable as regressors in the panel case. Lagged dependent variables are, however, not ruled out in the time series case (see Bai and Perron 1998).
Ditzen et al. (2021) use $\bar{x}_t = N^{-1} \sum_{i=1}^N x_{i,t}$ and $\bar{w}_t = N^{-1} \sum_{i=1}^N w_{i,t}$, and therefore so do we. The appropriately augmented version of (1) is therefore given by
\[ y_{i,t} = x_{i,t}' \beta + w_{i,t}' \delta_j + \bar{x}_t' a_i + \bar{w}_t' b_{i,j} + \text{error}. \] (6)

Because asymptotically observing the cross-sectional averages is just as good as observing the true factors, the regressors in (6) are asymptotically exogenous. This means that the estimation can be carried out using OLS. This is the same idea as in the “common correlated effects” (CCE) estimator of (Pesaran 2006), with the difference that here we do not include the cross-sectional average of $y_{i,t}$ as a regressor in (6) (see Karavias et al. 2021, for a discussion). If $f_t$ is neither completely known, nor completely unknown, as is usually the case in practice, then the cross-sectional averages will take care of the unknown factors and the known factors can be added to (6) as additional regressors.

If $N = 1$, such that (1) is a time series model, then by definition there is no cross-sectional variation that we can exploit to estimate unknown factors. Hence, in this case $f_t$ must be known, and hence the model to be estimated is given by (5), which is then the same as in Bai and Perron (1998).

3 The toolbox

3.1 Hypotheses testing

This section presents the first set of tools, which are necessary for establishing that structural change has happened and for determining the number of structural breaks, $s$. In particular, we consider tests of three hypotheses, labelled “(A)”–“(C)”, and a sequential test to determine $s$. We begin by stating the hypotheses of interest.

(A) $H_0$: no breaks versus $H_1$: $s$ breaks, where the number of breaks under $H_1$, $s$, is specified by the researcher.

(B) $H_0$: no breaks versus $H_1$: $1 \leq s \leq s_{\max}$ breaks, where the maximum number of breaks under $H_1$, $s_{\max}$, is specified by the researcher.

5. Take the so-called “wage curve” model, which relates worker’s wages to the rate of unemployment, and is the most common motivating example in the literature (see, for example, Bai, 2009). Here the factor loadings may represent workers’ unobservable skills, such as innate ability, perseverance, and motivation, and the factors would represent the price of these skills, which are not necessarily constant over time.

6. The intuition for why argumentation by $\bar{x}_t$ is needed is simple. We begin by noting that by (3), $\bar{x}_t = \Gamma_x' f_t + \bar{u}_{x,t}$, where $\Gamma_x$ and $\bar{u}_{x,t}$ are the cross-sectional averages of $\Gamma_{x,i}$ and $u_{x,i,t}$, respectively. Hence, provided that $u_{x,i,t}$ is mean zero and independent across $i$, by a central limit law, $\bar{x}_t \rightarrow_p \Gamma_x' f_t$ as $N \rightarrow \infty$, where $\rightarrow_p$ signify convergence in probability. We say that $\bar{x}_t$ is “rotationally consistent” for $f_t$, which is enough if the purpose is to control for $f_t$. The intuition for why $\bar{w}_t$ is need is analogous.

7. The cross-sectional averages can in principle capture all factors, regardless of whether they are observed (known) or not. An important condition for this to work is, however, that the number of cross-section averages is not fewer than the number of factors they replace. Because of this it is a good idea to treat known factors as additional regressors in (6), as it makes it possible to estimate more unknown factors.
(C) $H_0$: $s$ breaks versus $H_1$: $s + 1$ breaks, where $s$ is specified by the researcher.

To test hypotheses (A)–(C) we employ a number of test statistics. The time series versions of these tests have appeared in Bai and Perron (1998), while the panel versions have appeared in Ditzen et al. (2021).

**Hypothesis (A)**

If the dates of the breaks are known, the test that we are going to consider for hypothesis (A) is simply a Chow test. Let us therefore denote by $F(T_s)$ the $F$-statistic for testing the null of no breaks versus the alternative of $s$ known breaks at dates $T_s$, which in the time series case is based on (5), while in the panel case it is based on (6). Appropriate critical values can be taken from the $F$-distribution with $s$ numerator degrees of freedom and $N(T - p - (s + 1)q) - p - (s + 1)q$ denominator degrees of freedom.

If $T_s$ is unknown, which is most likely in practice, then the following supremum statistic is used:

$$\sup F(s) = \sup_{T_s \in T_{s,\epsilon}} F(T_s).$$

(7)

Here

$$T_{s,\epsilon} = \{ (T_1, ..., T_s) : T_{j+1} - T_j \geq \epsilon T, T_1 \geq \epsilon T, T_s \leq (1 - \epsilon)T \},$$

(8)

is the set of permissible break dates with $\epsilon$ being a user-defined trimming parameter. By setting $\epsilon \in (0, 1)$ we ensure that the breaks considered in the test are distinct and bounded away from the sample endpoints, as assumed.

**Hypothesis (B)**

Hypothesis (B) can be tested using the following double maximum statistic:

$$\text{WDmax} F(s_{\text{max}}) = \max_{1 \leq s \leq s_{\text{max}}} \frac{c_{\alpha,1}}{c_{\alpha,s}} \sup F(s),$$

(9)

where $c_{\alpha,s}$ is the critical value of $\sup F(s)$ at significance level $\alpha$ and $s$ breaks. The weighting by $c_{\alpha,1}/c_{\alpha,s}$ here ensures that the marginal $p$-values of the weighted supremum statistics are all equal. This counterweights the decrease in the marginal $p$-value of $\sup F(s)$ that comes from increasing $s$, and the resulting loss of power when $s$ is large.

The test statistic can also be unweighted in which case we set $c_{\alpha,1}/c_{\alpha,s} = 1$ for all $s$.

**Hypothesis (C)**

In Section 4 we describe a procedure for how to estimate the break dates. Let $\hat{T}_s = \{\hat{T}_1, ..., \hat{T}_s\}$ be the set of estimated breaks obtained based on that procedure. For the test of hypothesis (C) we use the following statistic:

$$F(s + 1|s) = \sup_{1 \leq j \leq s + 1, \tau \in T_s} F(\tau|\hat{T}_s).$$

(10)
where \( \hat{T}_s \) contains estimates of the \( s \) break stipulated under the hull hypothesis, \( \tau \) is the additional \((s+1)\)-th break under the alternative, and

\[
\hat{T}_{j,\epsilon} = \left\{ \tau : \hat{T}_{j-1} + (\hat{T}_j - \hat{T}_{j-1})\epsilon \leq \tau \leq \hat{T}_j - (\hat{T}_j - \hat{T}_{j-1})\epsilon, \hat{T}_0 = 0, \hat{T}_{s+1} = 1 \right\}
\]

(11)
is the set of permissible breaks in between the estimated \((j-1)\)-th and \( j \)-th breaks. Hence, \( F(s+1|s) \) is testing the null of \( s \) breaks versus the alternative that there is an additional break somewhere within the regimes stipulated under the null. Finally, \( F(\tau|\hat{T}_s) \) is the \( F \)-statistic based on taking the estimated break dates in \( \hat{T}_s \) as given and testing for one additional break at \( \tau \).

The \( F(s+1|s) \) test can be applied sequentially to estimate the number of breaks. In this case, we start by testing the null of no breaks against the alternative of a single break using \( F(1|0) \). If the null is accepted, we set \( \hat{s} = 0 \) and terminate the procedure. If, however, the null is rejected, we estimate the breakpoint, denoted \( \hat{T}_1 \), and split the sample in two at \( \hat{T}_1 \). We then test for the presence of a break in each of the two subsamples using \( F(2|1) \). If no breaks are found, we set \( \hat{s} = 1 \) and stop, whereas if breaks are detected, we estimate their location and split the sample again. This process continues until the test fails to reject.

The asymptotic distributions of the above tests in the pure time series and panel cases can be found in Bai and Perron (1998), and Ditzen et al. (2021), respectively. Because the distributions are the same, so are the critical values. \texttt{xtbreak} therefore uses the critical values of Bai and Perron (1998), and Bai and Perron (2003), which are applicable for \( \epsilon \in \{0.05, 0.1, 0.15, 0.2, 0.25\} \). In theory, the validity of the critical values requires \( T \to \infty \) in the time series case and \( N, T \to \infty \) with \( T/N \to 0 \) in the panel case, which in practice means that \( T \) should be “large” in both cases, and that \( N \) should be even larger in the panel case. For some Monte Carlo evidence on the accuracy of these predictions, we make reference to Bai and Perron (2003), and Ditzen et al. (2021).

## 4 Break date estimation

The previous section was focused on testing for the existence of breaks, and on determining their number. As soon as a number of breaks is detected, interest turns to their location, as it is the dates of the breaks that researchers use to identify the underlying cause of change.

The standard approach in the literature is to estimate breaks by minimizing the sum of squared residuals. Bai and Perron (1998), and Ditzen et al. (2021) do the same. The break date estimator included in \texttt{xtbreak} is therefore given by

\[
\hat{T}_s = \arg \min_{\tau \in T_s, \epsilon} SSR(\hat{T}_s),
\]

(12)

where \( SSR(\hat{T}_s) \) is the sum of squared residuals based on \( s \) breaks. In the time series case the residuals are taken from (5), whereas in the panel case they are taken from (6). If \( s \) is “small”, the minimization can be done by grid search. If, however, \( s \) is “large”, then grid search, which requires \( O(T^2) \) OLS operations, becomes computationally very
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costly and possibly even infeasible. In such cases, the efficient dynamic programming
algorithms of Bai and Perron [1998, 2003], and Ditzen et al. [2021], which limit
the number of operations to $O(T^2)$ for any $s$, can be used.

Once $\hat{T}_s$ has been obtained, confidence intervals for each estimated break date can
be constructed using the formulas given in Bai and Perron [1998], and Ditzen et al.
[2021].

5 The xtbreak command

5.1 Syntax

Automatic estimation of number of breaks and breakdates

xtbreak depvar [indepvars] [if] [, options1 options2 options5 ]

estimates the number of breaks and breakdates with no prior knowledge on number
and location of breaks. Estimation of the number of breaks is based on the sequential
test of Hypothesis (C).

Testing for known structural breaks

xtbreak test depvar [indepvars] [if] [, breakpoints(numlist|datelist
   [,index|fmt(string)]) options1 options5 ]

implements Hypothesis (A): testing for breaks if the break dates are known.

Testing for unknown structural breaks

xtbreak test depvar [indepvars] [if] [, hypothesis(1|2|3) breaks(real)
   options1 options2 options3 options4 options5 ]

implements Hypotheses (A)-(C): testing for breaks if the break dates are unknown.

Estimation of breakdates

xtbreak estimate depvar [indepvars] [if] [, breaks(real) showindex
   options1 options2 options5 ]

estimates breakdates for a given number of breaks.
Updating `xtbreak`

`xtbreak update`

obtains the latest version from GitHub.

**Specific Options**

`options1` are general options and apply to `xtbreak` in general:

```
breakconstant  noconstant  nobreakvariables(varlist1) vce(type)
```

`options2` are specific for unknown break dates:

```
trimming(real)
```

`options3` are specific for unknown break dates and hypothesis(2):

```
wmax level(#)
```

`options4` are specific for unknown break dates and hypothesis(3):

```
sequential
```

`options5` are panel data specific:

```
breakfixedeffects  nofixedeffects  csd  csa(varlist)  csanobreak(varlist)
kfactors(varlist) nbkfactors(varlist)
```

Data must be [XT] `tsset` or [XT] `xtset` before using `xtbreak`. `depvar`, `indepvars` and `varlist` may contain time-series operators, see [TS] `tsvarlist`.

### 5.2 Description of options

`breakpoints(numlist|datelist [,index|fmt(format)])` specifies the known breakpoints. Known breakpoints can be set by either the number of the corresponding observations or by the values of the time identifier. If a `numlist` is used, option index is required. For example, `breakpoints(10,index)` specifies that the one break occurs at the 10-th observation in time. `datelist` takes a list of dates. For example, `breakpoints(2010Q1, fmt(tq))` specifies a break in the first quarter of 2010. The option `fmt()` specifies the format and is required if a datelist is used. The format set in `breakpoints()` and the time identifier needs to be the same.

`breaks(#)` specifies the number of unknown breaks under the alternative. For hypothesis (B), `breaks()` can include two values. For example, `breaks(4 6)` amounts to testing the null of no breaks against the alternative of 4–6 breaks. If only one value specified, then the lower bound of the number of breaks under the alternative is set to 1. If hypothesis (C) is tested, then `breaks()` defines the number of breaks under the alternative. If the sequential test approach is used, then `breaks()` is maximum number of breaks.
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showindex show confidence intervals as index.

hypothesis(1|2|3) specifies which hypothesis to test. Specify h(1) for hypothesis (A), h(2) for hypothesis (B) and h(3) for hypothesis (C).

breakconstant break in constant. Default is no breaks in the constant term.

noconstant suppresses constant.

breakfixedeffects break in individual fixed effects.

nofixedeffects suppresses individual fixed effects.

nobreakvariables(varlist1) defines variables with no structural breaks. varlist1 can contain time series operators.

vce(type) specifies the covariance matrix estimator. The options are: ssr (homoskedastic errors), hac (heteroskedastic and autocorrelation robust), hc (heteroskedastic robust) and np (the non-parametric estimator of Pesaran 2006).

trimming(string) specifies the trimming parameter in percent. The trimming affects the minimal time periods between two breaks. The default is 15% (0.15). Critical values are available for %5, 10%, 15%, 20% and 25%.

wdmax weights the double maximum test statistic used for testing hypothesis (B). The default is not to use any weights.

level(#) sets the significance level for critical values for the double maximum test. If a value is chosen for which no critical values exits, xtbreak test will choose the closest level.

csa(varlist) specifies the variables with breaks which are added as cross-sectional averages. xtbreak calculates internally the cross-sectional averages.

csanobreak() is the same as csa() but for variables without a break.

csd implements csa(w) csanobreak(x) automatically. For example, the variables in w would enter with breaks, while those in x, specified with the nobreakvariables(varlist1), enter without breaks.

kfactors(varlist) Variables in varlist are known factors, variables in the data which are constant across the cross-sectional dimension. Examples are seasonal dummies or other observed common factors such as asset returns and oil prices. The factors in this list are affected by structural breaks in that their loadings change.

nbkfactors(varlist) Same as above, but the factors in this list are not affected by structural breaks.

xtbreak detects automatically if N = 1 or N > 1. The user therefore does not have to specify if the data have a time series or a panel structure.
5.3 Stored values

`xtbreak estimate` stores the following in `e()`:

Matrices
- `e(breaks)` Matrix with break dates
- `e(CI)` Confidence intervals with dimension \(4 \times \text{number_breaks}\)

`xtbreak test` stores the following in `r()` for known breakpoints:

Scalars
- `r(Wtau)` Value of test statistic
- `r(p)` \(p\)-value from \(F\) distribution

For unknown breakpoints the following is stored:

Scalars
- `r(supWtau)` Value of the \(\sup F(s)\) statistic (hypothesis (A))
- `r(Dmax)` Value of unweighted double maximum test statistic (hypothesis (B))
- `r(WDmax)` Value of weighted double maximum test statistic (hypothesis (B))
- `r(f)` Value of the \(F(s + 1|s)\) statistic (hypothesis 3)
- `r(c90)` Critical value at the 90% level
- `r(c95)` Critical value at the 95% level
- `r(c99)` Critical value at the 99% level

5.4 Postestimation

The following postestimation commands can be used after `xtbreak estimate`:

- **estat indicator** [newvar]

  creates an indicator variable \((1, \ldots, 1, 2, \ldots, 2, \ldots, s+1, \ldots, s+1)^\prime\) that specifies all break regimes. To split a varlist according to the estimated breakpoints

- **estat split varlist**

  and to draw a scatter plot of the variable with break on the x-axis and the dependent variable in the y-axis:

- **estat scatter varname**

  **estat indicator** creates a new variable of the form \((1, \ldots, 1, 2, \ldots, 2, \ldots, s+1, \ldots, s+1)^\prime\) and where the value changes for each break regime. **estat split** splits the variables defined in varlist according to the breakdates. **estat split** saves the names of the created variables in `r(varlist)`. **estat scatter** draws a scatter plot with the dependent variable on the y-axis and a variable with breaks defined in `varname` on the x-axis.
5.5 On the choice of factors in the panel case

`xtbreak` is versatile in dealing with common factors through the options `csd`, `csa()`, `csanobreak()`, `kfactors()` and `nkfactors()`. It allows for both known and unknown factors. Unknown factors are estimated by the cross-sectional averages specified in `csa()` and `csanobreak()`, or alternatively in `csd`. Known factors can be dummy variables, and other observed variables that are common to all cross-sectional units and are defined by `kfactors()` and `nkfactors()`. Whenever available, such factors should be included as they make it possible to estimate more unknown factors. These factors can be free of breaks or they can be allowed to be affected by the break. Fixed effects are known factors but are treated differently, though, because of their wide use and in order for `xtbreak`'s command structure to be similar to the rest of the Stata commands. In particular, one has to specify whether `xtbreak` should estimate a model with or without overall constant/individual fixed effects. In total, `xtbreak` supports five different models depending on this specification. There are presented in Table 1. The default is a model with fixed effects.

| Specification                   | Options                     |
|--------------------------------|-----------------------------|
| Individual fixed effects       | noconstant*                 |
| Fixed effects with breaks      | breakfixedeffects noconstant|
| Overall constant               | nofixedeffects              |
| Constant with breaks           | breakconstant nofixedeffects|
| Nothing                        | noconstant nofixedeffects   |

Notes: * is the default. Option `noconstant` not necessary.

Table 1: Constant/fixed effects model specifications.

The choice of deterministic model has implications for the structural break analysis. In the constant-only model, the constant is treated as a regular regressor and we can test and detect breaks in it. In fact, the constant may be the only regressor. With fixed effects, `xtbreak` cannot consider a model without breaking regressors ($w_{i,t}$) and it cannot detect or estimate breaks that affect only the fixed effects and not the regressors. However, the analysis of the breaking regressors is unaffected should some or indeed all breaks affect the fixed effects.

6 Empirical application to COVID–19 deaths and cases

6.1 Time series evidence for the whole US

Main results

In this section, we explain the use and options of `xtbreak`. We want to test if we can identify structural breaks in the relationship between the number of COVID–19 deaths and cases in the US in 2020 and 2021. To do so we use weekly data on the number of deaths and new cases from the [CDC](https://www.cdc.gov). The dataset is also available on our [GitHub](https://github) page.
We want to estimate the following model:

\[ \text{DEATHS}_t = \beta_0 + \delta_1 \text{CASES}_{t-1} + \text{error}, \]  

where \( \text{DEATHS}_t \) and \( \text{CASES}_t \) are the reported deaths due to COVID–19 in week \( t \) as defined by the CDC, and the number of new cases for the entire US in the same week, respectively. We assume that on average a week lies between a positive test and a possible death.\(^8\) The data ranges from 27 January 2020 (beginning of week 4) to 29 August 2021 (end of week 34).

We want to test if \( \beta_0 \) and \( \delta_1 \) are exposed to structural changes. There are several reasons for believing that the relationship between the number of new cases and deaths might have changed. In the beginning of the pandemic the understanding and best way to treat the disease was not very developed. The numbers were also under-reported due to limits in testing capacity and reporting routines. With better testing capacity, reporting routines and treatments, the relationship is expected to change, especially after the first two waves, because of the knowledge gained. Starting in mid-December

\(^8\) Note that since we use weekly data, the difference can be up to 13 days. Monday is taken as the first day of a given week.
Structural Breaks in Stata

2020, vaccines were introduced, and hence the relationship between the number of cases and deaths might be expected to have changed again. It therefore seems reasonable to expect at least two breaks.

Figure 1 plots the number of deaths and cases over time. The first thing to note is the striking difference between the number of deaths and cases in the first wave with the number of deaths being many times larger than the number of new cases. This difference is markedly smaller in the second wave but still the number of deaths is highest. The third wave was the worst in terms of numbers by far, but the number of deaths per new case was much lower than before. From about week 29 in 2020 the number of cases started to pick up again, and so did the number of deaths.

We can use `xtbreak` without any prior knowledge of the number of breaks or their exact dates. We use the following command line:

```
. xbreak deaths L.cases
```

### Sequential test for multiple breaks at unknown breakpoints
(\cite{Ditzen2021})

| Test | Statistic | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|------|-----------|-------------------|-------------------|--------------------|
| F(1|0) | 107.50    | 12.29             | 8.58              | 7.04               |
| F(2|1) | 31.25     | 13.89             | 10.13             | 8.51               |
| F(3|2) | 6.96      | 14.80             | 11.14             | 9.41               |
| F(4|3) | 1.18      | 15.28             | 11.83             | 10.04              |
| F(5|4) | 4.95      | 15.76             | 12.25             | 10.58              |

Detected number of breaks: 2 2 2

The detected number of breaks indicates the highest number of breaks for which the null hypothesis is rejected.

### Estimation of break points

\[
\begin{align*}
T & = 82 \\
SSR & = 226.85 \\
\text{Trimming} & = 0.15
\end{align*}
\]

| # | Index | Date       | [95% Conf. Interval] |
|---|-------|------------|----------------------|
| 1 | 16    | 2020w20    | 2020w19              | 2020w21              |
| 2 | 59    | 2021w11    | 2021w9               | 2021w13              |

`xtbreak` determines the number of breaks using the sequential testing approach described in Section 3.1. The maximum number of breaks is \( s_{\text{max}} = 5 \). It reports the test value at each step in the sequence and the appropriate critical value. The number of breaks is increased by one every time the test is able to reject the null, starting at 0 breaks. We see that 0 breaks is rejected in favour of at least 1 break and that 1 break

---

9. The maximum permissible number of breaks depends on the minimal length of the subsamples considered, and hence on the trimming parameter \( \epsilon \). The maximum number of breaks is given by the formula \( \lceil \frac{1}{\epsilon} \rceil - 2 \), where \( \lceil \cdot \rceil \) is the smallest greater integer function. For \( \epsilon = 0.10 \) it is 8 and for \( \epsilon = 0.05 \) it is 18.
Figure 2: Plotting estimated breaks (dashed lines), 95% confidence intervals (dotted lines), deaths and lagged cases.

is rejected in favour of at least 2 breaks, but then when testing 2 breaks against 3 or more breaks the test is no longer able to reject. We therefore conclude that there are 2 breaks. We also get the estimated break dates and the associated confidence intervals. The first break is estimated to week 20 of 2020 (third week of May), while the second is estimated to week 11 of 2021 (third week of March). The confidence intervals on both breaks span only a couple of weeks, suggesting that the estimates are precise.

xtbreak saves the values of the breakpoints in e(breaks) and the confidence intervals in e(CI). The matrices contain the index number $t \in \{1, \ldots, T\}$ of the breaks and the bound of the confidence intervals. We can use this information to draw Figure 2 in which the estimated break dates and their 95% confidence intervals are plotted in the same graph as the deaths and the lagged number of cases.

Next we can use the estat function of xtbreak to generate new variables for each break regime and run a simple OLS regression:

```stata
   . estat split
   New variables created: L_cases1 L_cases2 L_cases3
```

10. The code is available in the accompanying do file.
The estimate for the first regime covering the period from week 4 of 2020 to week 20 of 2020 suggests that for each additional 1,000 COVID–19 cases around 59 people died. According to Figure [2], the end date of this regime coincides with the end of the first wave. This estimate is quite high, which can be explained by the relatively small number of tests conducted at that time. The estimated effect of the number of cases is much lower in the second regime, which stretches week 21 of 2020 to week 10 of 2021. Only 14 out of an additional 1,000 infected died. In the third and last regime, which starts in week 11 of 2021, the estimated effect reduces even further, to 6 deaths per 1,000 infected. This is probably partly due to vaccination roll-out, which began in week 51 of 2020.

**Additional results and discussions**

This section is divided in two; (i) additional test results and (ii) additional estimation results. We begin by considering some additional test results, starting with a test of hypothesis (A). Specifically, we test the null hypothesis of no breaks against the alternative of a break in week 20 in 2020 and another break in week 11 in 2021 using the regular Chow $F$-test. There are the results:

```
.xtbreak test deaths L.cases , hypothesis(1) breakpoints(2020W20 2021W11, fmt(tw))
```

Test for multiple breaks at known breakdates
(Bai & Perron. 1998. Econometrica)
H0: no breaks vs. Hi: 2 break(s)
\[ W(\tau) = 134.70 \]
\[ p-value (F) = 0.00 \]

The test value is 134.7, which is way out in the critical region of the $F$ distribution. We can therefore comfortably reject the null of no breaks. To test the same hypothesis but with unknown break dates, we specify `breaks(2)`. The results look as follows:

```
.xtbreak test deaths L.cases , hypothesis(1) breaks(2)
```

Test for multiple breaks at unknown breakdates
The test value is identical to before, as is the conclusion to reject the null hypothesis, which is to be expected because the given break dates were set to the estimated breaks obtained earlier. The difference is that when the breaks are treated as unknown, the critical values come from a non-standard distribution, because the statistic is the supremum of $F$-tests over all possible break dates, as these are determined by the trimming parameter. These critical values are more “honest” than those used for the Chow test, as they account for the fact that the breaks are unknown. As a part of the test results, `xtbreak` reports the estimated break dates used to construct the test, and we can see that they coincide with those obtained earlier.

We now test the null of no breaks against the alternative of up to 5 breaks. This is an example of a test of hypothesis (B), the results of which are presented here below. As expected, the null hypothesis is firmly rejected.

```
. xtbmex test deaths L.cases , hypothesis(2) breaks(5)
Test for multiple breaks at unknown breakdates
(Bai & Perron. 1998. Econometrica)
H0: no break(s) vs. H1: 1 <= s <= 5 break(s)

| Test Statistic | Bai & Perron Critical Values |
|----------------|-------------------------------|
| supW(tau)      | 134.70 9.36 7.22 6.28        |
```

Estimated break points: 2020w20 2021w11
Trimming: 0.15

Next, we test the null of 2 breaks against the alternative of 3 breaks, which is an example of hypothesis (C). We use the options `hypothesis(3)` and `breaks(3)` to specify that there are 3 breaks under the alternative. The results presented below suggest that we are unable to reject the null, which is consistent with the estimated number of breaks.

```
. xtbmex test deaths L.cases , hypothesis(3) breaks(3)
Test for multiple breaks at unknown breakpoints
(Bai & Perron. 1998. Econometrica)
H0: 2 vs. H1: 3 break(s)

| Test Statistic | Bai & Perron Critical Values |
|----------------|-------------------------------|
| UDmax(tau)     | 149.05 12.37 8.88 7.46       |
* evaluated at a level of 0.95.
Trimming: 0.15
```
Structural Breaks in Stata

| F(s+1|s)* | 6.96 | 14.80 | 11.14 | 9.41 |
|---------|------|-------|-------|------|

* s = 2
Trimming: 0.15

The sequential test results reported earlier can be obtained using the option `sequential` with up to 5 breaks specified by the option `breaks(5)`. The appropriate command line is the following:

```
xtbreak test deaths L.cases , hypothesis(3) breaks(5) sequential
```

As a final test exercise, we consider two changes to the model. We begin by investigating how the above results are affected if we allow for breaks in the constant. To do so we use the sequential test but add the option `breakconstant`:

```
xtbreak test deaths L.cases , breakconstant
```

To save space we omit the output, but we briefly describe it. `xtbreak` finds one break, which if we investigate further occurs in week 20 of 2020. We also investigate if the break is only in the constant, but not in the number of cases. We keep the option `breakconstant` and move the variable `L.cases` to the option `nobreakvar(L.cases)`:

```
xtbreak test deaths , breakconstant nobreakvar(L.cases)
```

Again, `xtbreaks` detects one break which in this case is dated to week 22 of 2020. The confidence intervals of the last two examples both include week 20 of 2020.

We end this section with some comments on the estimation results. The break date results reported earlier can be obtained using the option `xtbreak estimate`. The appropriate command line is the following:

```
xtbreak estimate deaths L.cases , breaks(2)
```

As an illustration of the estimated regression model, we can draw a scatter plot with different colours for the observations within each regime. The plot can be created using `xtbreak estat`;

```
. estat scatter L.cases
```

The plot is displayed in Figure 3. The different colored markers represent the observations within each regime, and the shape of the observations is indicative of the strength of the estimated linear relationships and of their slopes. In particular, we see that the slopes differ quite markedly between regimes, which confirms the findings from the OLS regression.
Figure 3: Scatter plotting lagged cases against deaths by regime.
6.2 State level panel evidence

Main results

In this section, we use the same US data as in the previous section; however, instead of aggregating the data up to the country level, we use data for all 50 US states, the District of Columbia, New York City, overseas territories and three countries in free association with the US.

Similarly to before, we begin by reporting some results based on the sequential test to estimate the number of breaks and the estimated break dates. To account for potential heteroskedasticity and autocorrelation we use robust (HAC) standard errors. `xtbreak` automatically detects if a panel data model is used, and thus the syntax remains the same. These are the results:

```
. xtbond deaths L.cases, vce(hac)
```

### Sequential test for multiple breaks at unknown breakpoints
(Ditzen, Karavias & Westerlund. 2021)

| Test Statistic | Bai & Perron Critical Values |
|----------------|-----------------------------|
|                | 1% Critical Value | 5% Critical Value | 10% Critical Value |
| F(1|0)            | 29.59             | 12.29             | 8.58              | 7.04              |
| F(2|1)            | 37.75             | 13.89             | 10.13             | 8.51              |
| F(3|2)            | 10.88             | 14.80             | 11.14             | 9.41              |
| F(4|3)            | 21.38             | 15.28             | 11.83             | 10.04             |
| F(5|4)            | 8.29              | 15.76             | 12.26             | 10.58             |

Detected number of breaks: 4 4 4

The detected number of breaks indicates the highest number of breaks for which the null hypothesis is rejected.

Estimation of break points

| # | Index | Date   | [95% Conf. Interval] |
|---|-------|--------|----------------------|
| 1 | 15    | 2020w19| 2020w18 2020w20     |
| 2 | 34    | 2020w38| 2020w37 2020w39     |
| 3 | 47    | 2020w51| 2020w50 2020w52     |
| 4 | 59    | 2021w11| 2021w10 2021w12     |

We see that the first time the null hypothesis cannot be rejected at the 1% and 5% levels is when 2 breaks is tested against 3, implying 2 breaks. However, we also see that 3 breaks is rejected against 4, suggesting that the model might contain more than 2 breaks. The test procedure stops at 4 breaks, but with 15% (default) trimming.

---

11. The overseas territories and three countries are; American Samoa, Guam, the Commonwealth of the Northern Mariana Islands, Puerto Rico, the US Virgin Islands, the Federated States of Micronesia, Republic of the Marshall Islands, and Republic of Palau.
this is also the maximum number of breaks allowed. Because of this, we now change
the trimming from 15% to 10%, which will make the search finer. Also, since this is a
panel data set, we want to allow for the possibility that there might be cross-sectional
dependence. We therefore augment the model by the cross-section average of the lagged
number of cases. Now the results look as follows:

. xtbreak deaths L.cases, trimming(0.1) vce(hac) csa(L.cases)
Sequential test for multiple breaks at unknown breakpoints
(Ditzen, Karavias & Westerlund. 2021)

|   | Test Statistic | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|----------------|-------------------|-------------------|--------------------|
| F(1|0) | 10.80          | 13.00             | 9.10              | 7.42               |
| F(2|1) | 8.10           | 14.51             | 10.55             | 9.05               |
| F(3|2) | 12.77          | 15.44             | 11.36             | 9.97               |
| F(4|3) | 4.47           | 15.73             | 12.35             | 10.49              |
| F(5|4) | 9.27           | 16.39             | 12.97             | 10.91              |
| F(6|5) | 5.22           | 16.60             | 13.45             | 11.29              |
| F(7|6) | 5.05           | 16.78             | 13.88             | 11.86              |
| F(8|7) | 5.61           | 16.90             | 14.12             | 12.26              |
| F(9|8) | 4.89           | 16.99             | 14.45             | 12.57              |

Detected number of breaks: . 3 3

The detected number of breaks indicates the highest number of
breaks for which the null hypothesis is rejected.

Estimation of break points

\[
\begin{align*}
N &= 60 \\
T &= 82 \\
SSR &= 25.99 \\
Trimming &= 0.10
\end{align*}
\]

Cross-section averages:

| # | Index | Date       | [95% Conf. Interval] |
|---|-------|------------|----------------------|
| 1 | 15    | 2020w19    | 2020w18              | 2020w20              |
| 2 | 47    | 2020w51    | 2020w50              | 2020w52              |
| 3 | 57    | 2021w9     | 2021w8               | 2021w10              |

According to the results, there are no rejections at the 1% level, suggesting a model
without breaks. However, that seems unlikely given the evidence of breaks reported so
far. In interest of conservativeness, we therefore focus on the results at the 5% and 10%
levels, which lead to the same conclusion; namely, 3 breaks.

**Additional results and discussions**

We start by testing the null of no breaks against to test the alternative of up to 5 breaks.
This is a test of hypothesis (B). [Bai and Perron 2003] recommend to always test this
hypothesis before applying estimating the number of breaks using the sequential test.
These are the results:
Structural Breaks in Stata

```
. xbreak test deaths L.cases, h(2) breaks(5) trimming(0.1) vce(hac) csa(L.cases)
Test for multiple breaks at unknown breakdates  
(Ditzen, Karavias & Westerlund. 2021)  
H0: no break(s) vs. H1: 1 <= s <= 5 break(s)  
```

| Test Statistic | Bai & Perron Critical Values | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|----------------|-------------------------------|-------------------|-------------------|-------------------|
| UDmax(\(\tau\)) | 12.20                         | 13.07             | 9.52              | 8.05              |

* evaluated at a level of 0.95.  
Trimming: 0.10  
Cross-section averages:  
with breaks: L.cases

As expected given the sequential test results, the test rejects at the 5% and 10% levels but not at the 1% level. This means that at the 5% and 10% levels of significance there is evidence of up to 5 breaks. Next, we test the hypothesis of no break against 1 break and then no break against 3 breaks. The results are reported below. We see that the null of no breaks can be rejected at a level of 5% in both cases, but that the evidence at the 1% level depends on the number of breaks under the alternative. With 3 breaks under the alternative, we reject also at the 1% level, which we take as evidence in support of our earlier finding of 3 breaks.

```
. xbreak test deaths L.cases, h(1) breaks(1) trimming(0.1) vce(hac) csa(L.cases)
Test for multiple breaks at known breakdates  
(Karavias, Narayan & Westerlund. 2021)  
H0: no break(s) vs. H1: 1 break(s)  
```

| Test Statistic | Bai & Perron Critical Values | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|----------------|-------------------------------|-------------------|-------------------|-------------------|
| supW(\(\tau\)) | 10.80                         | 13.00             | 9.10              | 7.42              |

Estimated break points: 2020w19  
Trimming: 0.10  
Cross-section averages:  
with breaks: L.cases

```
. xbreak test deaths L.cases, h(1) breaks(3) trimming(0.1) vce(hac) csa(L.cases)
Test for multiple breaks at unknown breakdates  
(Ditzen, Karavias & Westerlund. 2021)  
H0: no break(s) vs. H1: 3 break(s)  
```

| Test Statistic | Bai & Perron Critical Values | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|----------------|-------------------------------|-------------------|-------------------|-------------------|
| supW(\(\tau\)) | 12.20                         | 8.42              | 6.84              | 6.09              |

Estimated break points: 2020w19 2020w51 2021w9  
Trimming: 0.10  
Cross-section averages:  
with breaks: L.cases
We now take 3 breaks as given and proceed to estimate their locations. The results are reported below. The estimated breaks take place in week 19 of 2020, in week 51 of 2020, and in week 9 of 2021. The confidence intervals for all three breaks are narrow. When we compare these results to those reported earlier based on the time series data set for the whole US, we see that the first break date is almost identical, as is the third break in the panel data set and the second break in the time series data set. Hence, for two of the break dates, the panel data evidence reinforces the time series evidence reported earlier. However, the panel data set also suggests that two breaks are not enough, and that there is a need to account for a third break in week 51 of 2020. Thus is in mid-December 2020, which is just before the peak of the third wave, as shown in Figure\textsuperscript{II} The fact that the panel toolbox detects one break that is not picked up by the time series toolbox could be due to the gain in accuracy obtained by using the larger panel data set (see Ditzen et al.\textsuperscript{2021}).

\begin{verbatim}
. xtbmarried estimate deaths L.cases, breaks(3) trimming(0.1) vce(hac) csa(L.cases)
Estimation of break points
\end{verbatim}

| #  | Index | Date         | [95% Conf. Interval]         |
|----|-------|--------------|-----------------------------|
| 1  | 15    | 2020w19      | 2020w18 2020w20             |
| 2  | 47    | 2020w51      | 2020w50 2020w52             |
| 3  | 57    | 2021w9       | 2021w8 2021w10              |

Cross-section averages:

We now use \texttt{estat split L.cases} to generate new variables for each regime and fit a simple fixed effects OLS regression to each. For comparison, we also report some results based on the CCE estimator, which are obtained by using \texttt{xtdcce2} (Ditzen\textsuperscript{2018, 2021}). The results are reported below. The CCE estimator allows for interactive effects and is therefore more general than fixed effects OLS. Interestingly enough, however, the results are very similar. Similarly to the results reported earlier for the time series data set, we see that the estimated coefficients in the first regime, which corresponds to the first wave, are the highest. The coefficients drop in the second regime, which includes the relatively calm summer of 2020, only to increase again in the third regime, which is the peak of the third wave. In the fourth and final regime, the estimated coefficients drop markedly when compared to earlier regimes, which is most likely a vaccination effect.

\begin{verbatim}
. estat split L.cases
New variables created: L_cases1 L_cases2 L_cases3 L_cases4
. xtregr deaths `r(varlist)`, fe
Fixed-effects (within) regression  Number of obs = 4,920
Group variable: ID  Number of groups = 60
R-squared: Within = 0.8144

|                |                |
|----------------|----------------|
| Number of obs  | 4,920          |
| Number of groups | 60            |
| Obs per group:  |                 |
| min = 82       |                 |
\end{verbatim}
Figure 4: Plotting estimated breaks (dashed lines), 95% confidence intervals (dotted lines), deaths and lagged cases.
Between = 0.9721  avg = 82.0
Overall = 0.8565  max = 82

corr(u_i, Xb) = 0.3305  Prob > F = 0.0000

| deaths | Coefficient | Std. err. | t  | P>|t|  | [95% conf. interval] |
|--------|-------------|-----------|----|-------|---------------------|
| L_cases1 | 0.0745328 | 0.0008793 | 84.76 | 0.000 | 0.072809 - 0.0762566 |
| L_cases2 | 0.0123852 | 0.0001553 | 79.77 | 0.000 | 0.0120808 - 0.0126895 |
| L_cases3 | 0.0157277 | 0.000136 | 115.67 | 0.000 | 0.0154611 - 0.0159942 |
| L_cases4 | 0.0077951 | 0.0002327 | 33.50 | 0.000 | 0.0073389 - 0.0082512 |
| _cons  | 0.0172031 | 0.0018211 | 9.45 | 0.000 | 0.0136328 - 0.0207734 |

F test that all u_i=0: F(59, 4856) = 7.29  Prob > F = 0.0000

. estat split L_cases
New variables created: L_cases1 L_cases2 L_cases3 L_cases4
. xtdcce2 deaths `r(varlist)', pooled(`r(varlist)') cr(L.cases)
(Dynamic) Common Correlated Effects Estimator - Pooled
Panel Variable (i): ID  Number of obs = 4920
Time Variable (t): date  Number of groups = 60
Degrees of freedom per group: 0bs per group (T) = 82
without cross-sectional averages = 77
with cross-sectional averages = 76
Number of cross-sectional lags = 0  Prob > F = 0.00
variables in mean group regression = 4  R-squared = 0.82
variables partialled out = 120  Root MSE = 0.10
CD Statistic = 48.41  p-value = 0.0000

| deaths | Coef. Std. Err. | z   | P>|z|  | [95% Conf. Interval] |
|--------|-----------------|-----|-------|---------------------|
| Pooled: |                 |     |       |                     |
| L_cases1 | 0.0741296 | 0.0251753 | 2.94 | 0.003 | 0.024787 - 0.1234723 |
| L_cases2 | 0.0138424 | 0.0018463 | 7.50 | 0.000 | 0.0102237 - 0.017461 |
| L_cases3 | 0.0172933 | 0.0027377 | 6.32 | 0.000 | 0.0139276 - 0.020659 |
| L_cases4 | 0.0089277 | 0.0027913 | 3.20 | 0.001 | 0.0034567 - 0.0143986 |

Pooled Variables: L_cases1 L_cases2 L_cases3 L_cases4
Cross Sectional Averaged Variables: L_cases
Heterogenous constant partialled out.

7 Conclusion

This paper presents a new community contributed command, called xtbreak, which enable researchers to detecting breaks, and to estimate their number and location. The command can be applied to time series and panel data, and can hence be seen as a
complete break detection toolbox that is applicable regardless of the structure of the data. In our empirical illustration, we employ US country and state level data to investigate the relationship between the number of COVID–19 cases and deaths, which may well have changed as a result of improvements in testing capacity, reporting routines and treatments. While the time series data set suggests 2 breaks, the panel data set suggests 3. Moreover, 2 out of the 3 breaks detected using the panel data set coincide with those detected using the time series data set. Use of the relatively larger panel data therefore leads to the detection of an additional break that is not detected when using the time series data set.

8 How to install

The latest version of the `xtbreak` package can be obtained by typing the following in Stata:

```
net from https://janditzen.github.io/xtbreak/
```

Updates and further documentation can be found on GitHub.

9 Acknowledgements

We are grateful to all participants of the Swiss, German and US Stata User Group Meetings in 2020 and 2021. Ditzen acknowledges financial support from Italian Ministry MIUR under the PRIN project Hi-Di NET - Econometric Analysis of High Dimensional Models with Network Structures in Macroeconomics and Finance (grant 2017TA7TYC). Westerlund acknowledges financial support from the Knut and Alice Wallenberg Foundation through a Wallenberg Academy Fellowship.

10 References

Bai, B. Y. J., and P. Perron. 1998. Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, 66(1): 47–78.

Bai, J., and P. Perron. 2003. Computation and analysis of multiple structural change models. *Journal of Applied Econometrics* 18(1): 1–22.

Ditzen, J. 2018. Estimating dynamic common-correlated effects in Stata. *The Stata Journal* 18(3): 585 – 617.

Ditzen, J. 2021. Estimating long run effects and the exponent of cross-sectional dependence: an update to xtdce2. *The Stata Journal* 21(3): 687–707.

Ditzen, J., Y. Karavias, and J. Westerlund. 2021. Testing for Multiple Structural Breaks in Panel Data. Mimeo (available upon request).
Karavias, Y., J. Westerlund, and P. Narayan. 2021. Structural Breaks in Interactive Effects Panels and the Stock Market Reaction to COVID-19. Mimeo (available upon request).

Pesaran, M. H. 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* 74(4): 967–1012.

About the authors

Jan Ditzen is an Assistant Professor at the Faculty of Economics and Management of the Free University of Bozen-Bolzano, Italy. His research interests are in the field of applied econometrics and spatial econometrics, particularly cross-sectional dependence in large panels.

Yiannis Karavias is an Assistant Professor in financial economics at the University of Birmingham. His research focuses on panel data models and their applications in macroeconomics and finance. Methodological interests include structural change, threshold regression, non-stationarity, and optimal hypothesis testing.

Joakim Westerlund is a Professor at Lund University and at Deakin University. Joakim’s primary research interest is the analysis of panel data. He has mainly been concerned with the development of procedures for estimation and testing of non-stationary panel data, but more recently his interest has shifted towards the development of econometric tools for factor-augmented regression models.